Engaging Content
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# Syntax in Statistical Machine Translation

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at IIS Academia Sinica

# Overview of Syntax in SMT



- **Introduction**
- Syntax-based Translation Models
- Syntax-based Language Models
- Syntax-based Translation Evaluations
- Conclusion and Future Work

# Google Translate - An Example



日本和美国的关系

Relationship between Japan and the United States

日本外交政策和美国亚太再平衡的关系

Japan's foreign policy and the US Asia-Pacific rebalancing of relations

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When input sentences become longer, it is more difficult for the Google Translate to capture their syntax structures.

# Google Translate - An Example



Aiken, Milam, and Shilpa Balan. "An analysis of Google Translate accuracy." Translation journal 16.2 (2011): 1-3.

| Language Paris | → | ← |
|---|---|---|
| English – French | 91 | 92 |
| English – German | 77 | 86 |
| English – Italian | 87 | 89 |
| English – Japanese | 26 | 49 |
| English – Chinese | 17 | 49 |

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| English – French | 91 | 92 |
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Google Translate performs worse for language pairs with bigger difference in syntax structures.

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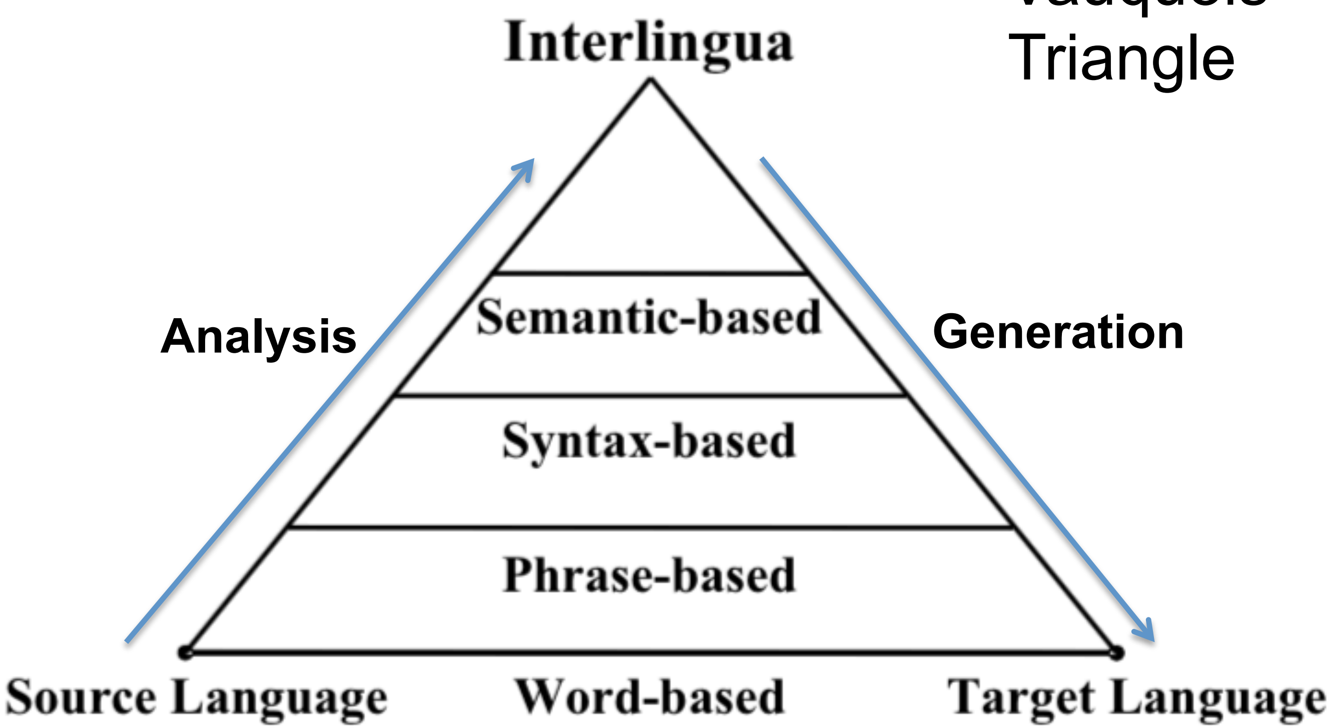
- **Syntax-based Translation Models**
- Syntax-based Language Models
- Syntax-based Translation Evaluations
- Conclusion and Future Work

# MT Pyramid



Vauquois' Triangle



# Word-based Models

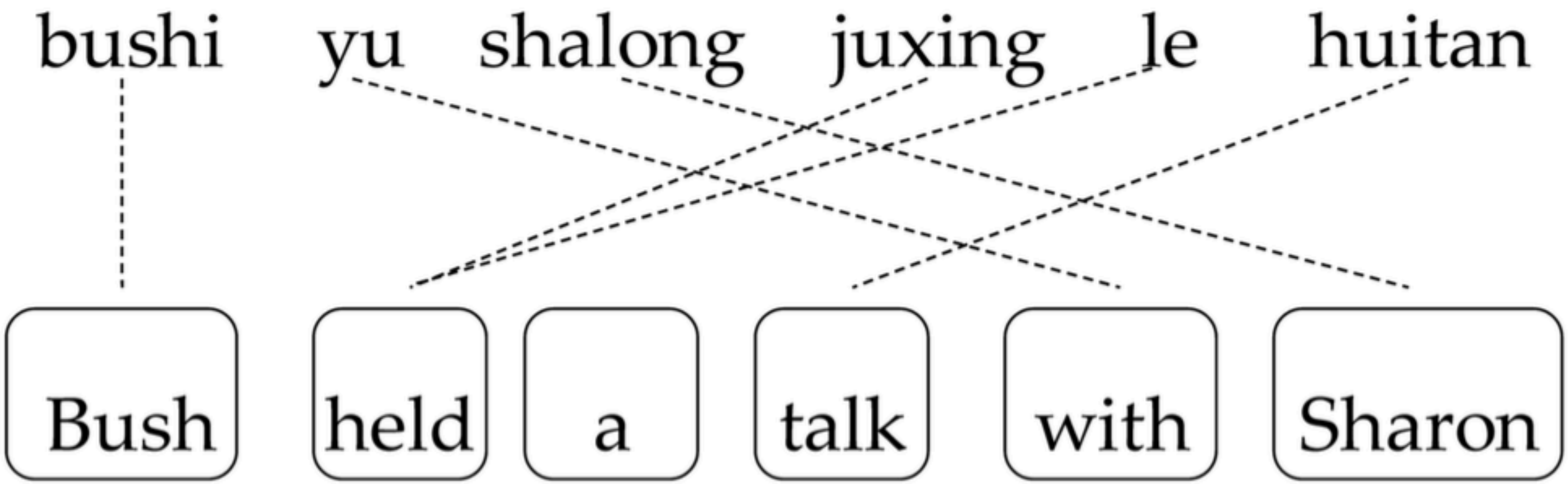


IBM Model 1-5

Peter F. Brown, Stephen A. Della Pietra, Vincent J. Della Pietra, and Robert L. Mercer. 1993. The Mathematics of Statistical Machine Translation: Parameter Estimation. Computational Linguistics, 19(2):263-311.

# Word-based Models

www.adaptcentre.ie



# IBM Models



| Source | Target | Probability |
|---|---|---|
| Bushi（布什） | Bush | 0.7 |
| | President | 0.2 |
| | US | 0.1 |
| yu（与） | and | 0.6 |
| | with | 0.4 |
| juxing（举行） | hold | 0.7 |
| | had | 0.3 |
| le（了） | hold | 0.01 |

# Phrase-based Models



## Phrase-based Model

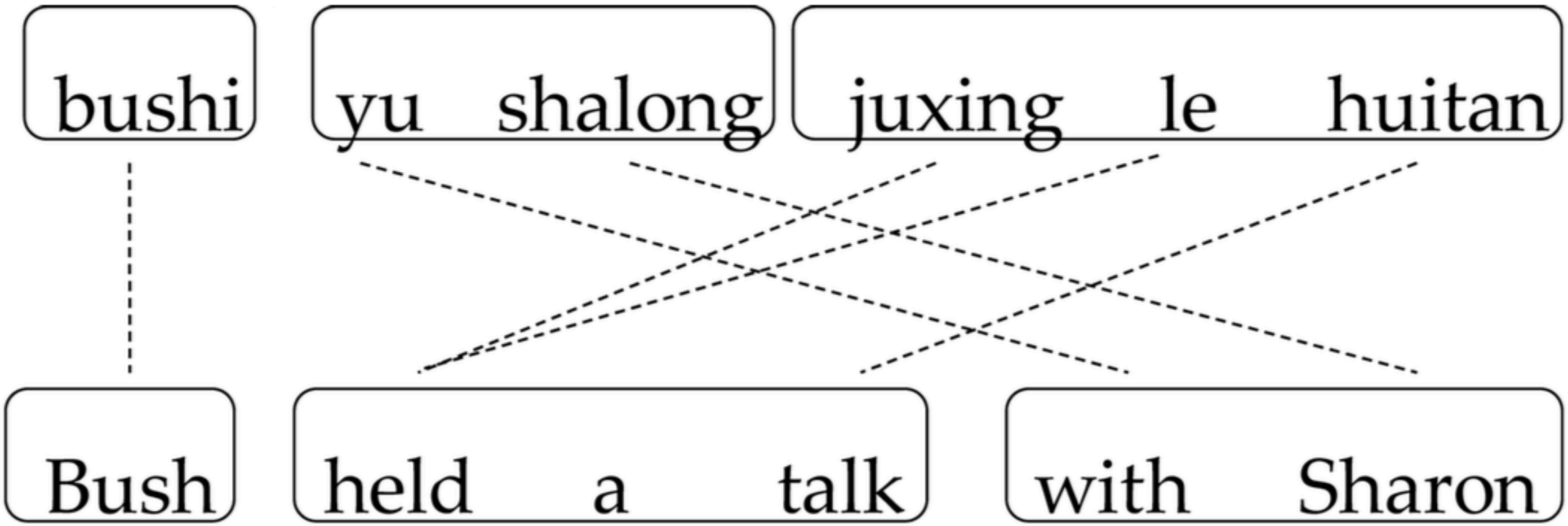
Philipp Koehn, Franz J. Och, and Daniel Marcu. 2003. Statistical Phrase-Based Translation. In Proceedings of the Human Language Technology and North American Association for Computational Linguistics Conference, pages 127-133, Edmonton, Canada, May.

## Alignment Template Model

Franz J. Och and Hermann Ney. 2004. The Alignment Template Approach to Statistical Machine Translation. Computational Linguistics, 30(4):417-449.

# Phrase-based Models





# Phrase-based Model



| Source | Target | Probability |
|---|---|---|
| Bushi （布什） | Bush | 0.5 |
| | president Bush | 0.3 |
| | the US president | 0.2 |
| Bushi yu （布什与） | Bush and | 0.8 |
| | the president and | 0.2 |
| yu Shalong （与沙龙） | and Shalong | 0.6 |
| | with Shalong | 0.4 |
| juxing le huiang （举行了会谈） | hold a meeting | 0.7 |
| | had a meeting | 0.3 |

# Syntax-based Model



Hierarchical Phrase-based Model

↓

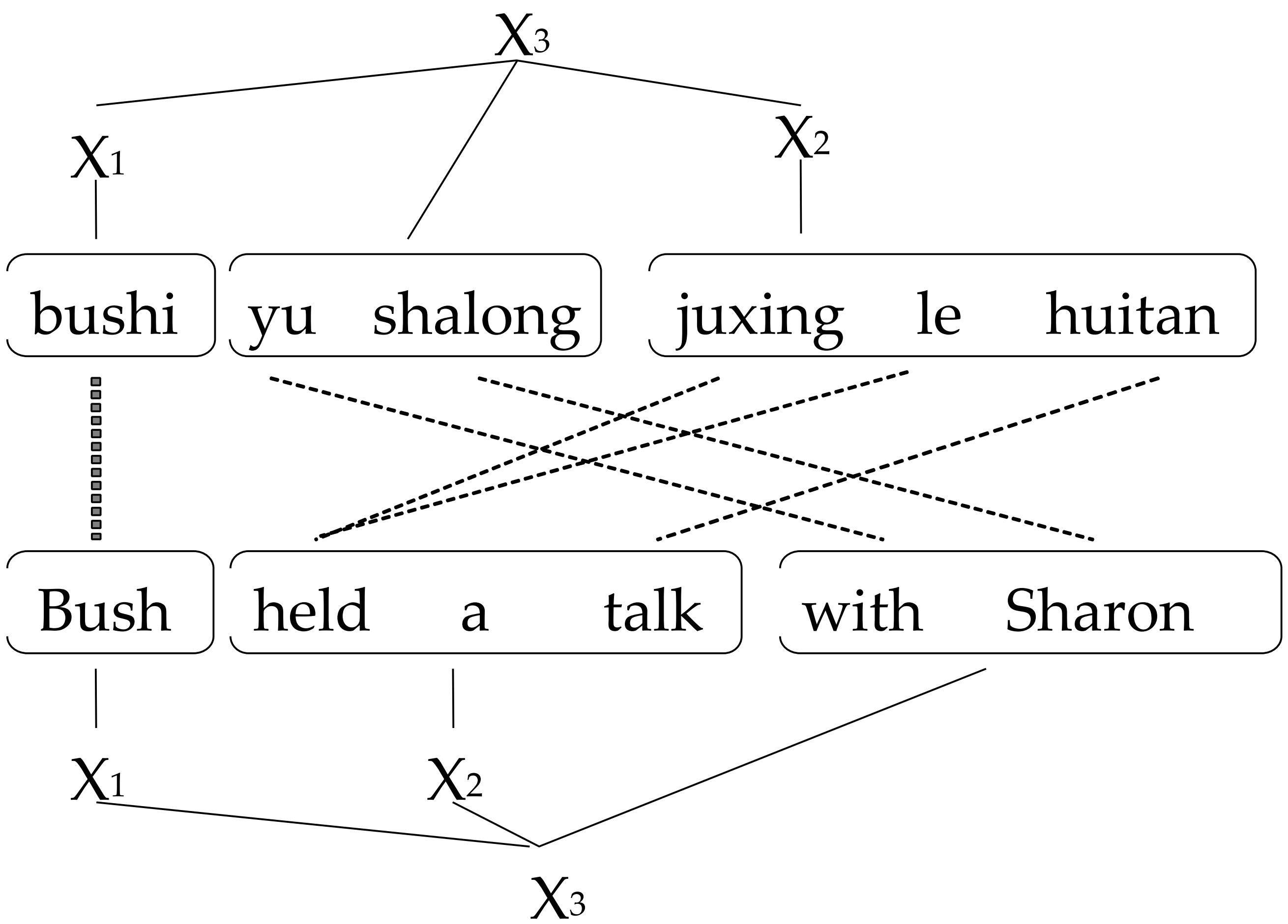
Constituent Syntax-based Model

↓

Dependency Syntax-based Model

# Hierarchical Phrase-based Model





# Hierarchical Phrase-based Model



| Source | Target | Probability |
|---|---|---|
| juxing le huiang （举行了会谈） | hold a meeting | 0.6 |
| | had a meeting | 0.3 |
| X huitang （X会谈） | X a meeting | 0.8 |
| | X a talk | 0.2 |
| juxing le X （举行了X） | hold a X | 0.5 |
| | had a X | 0.5 |
| Bushi yu Shalong （布什与沙龙） | Bush and Sharon | 0.8 |
| Bushi X （布什X） | Bush X | 0.7 |
| X yu Y （X与Y） | X and Y | 0.9 |

# Hierarchical Phrase-based Model



Advantage:

- Non-linguistic knowledge used
  - Language Independent
- High Performance
  - Synchronous CFG

Disadvantage:

- Limitation in long distance dependency
  - Use of Glue Rules for long phrases

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# Synchronous CFG



$$S \rightarrow \langle NP_{\boxed{1}}\ VP_{\boxed{2}},\ NP_{\boxed{1}}\ VP_{\boxed{2}} \rangle$$

$$VP \rightarrow \langle V_{\boxed{1}}\ NP_{\boxed{2}},\ NP_{\boxed{2}}\ V_{\boxed{1}} \rangle$$

$$NP \rightarrow \langle \text{i, watashi wa} \rangle$$

$$NP \rightarrow \langle \text{the box, hako wo} \rangle$$

$$V \rightarrow \langle \text{open, akemasu} \rangle$$

The implementation of decoding algorithm is straightforward – just like a parsing procedure, either CYK or Chart algorithm works

# Hierarchical Phrase-based Model



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# Glue Rules



$$S \rightarrow \langle S_{\boxed{1}} X_{\boxed{2}}, S_{\boxed{1}} X_{\boxed{2}} \rangle$$

$$S \rightarrow \langle X_{\boxed{1}}, X_{\boxed{1}} \rangle$$

- Using Glue Rules means sequentially concatenating all the target phrases, which lead to a back-off to phrase based model
- Two cases to use Glue Rules:
  - No hierarchical rules applicable
  - The span to be covered by the hierarchical rule is longer than a threshold

# Glue Rules



$$S \rightarrow \langle S_{\boxed{1}} X_{\boxed{2}}, S_{\boxed{1}} X_{\boxed{2}} \rangle$$

$$S \rightarrow \langle X_{\boxed{1}}, X_{\boxed{1}} \rangle$$

- Using Glue R
  concatenate a
  back-off to ph
- Two cases to use G es:
  - ➢ No hierarchical ules applicable
  - ➢ The span to be covered by the hierarchical rule is longer than a threshold

**Hierarchical Rules failed to capture dependency between words with a distance longer than a threshold**

# Syntax-based Model



Hierarchical Phrase-based Model

↓

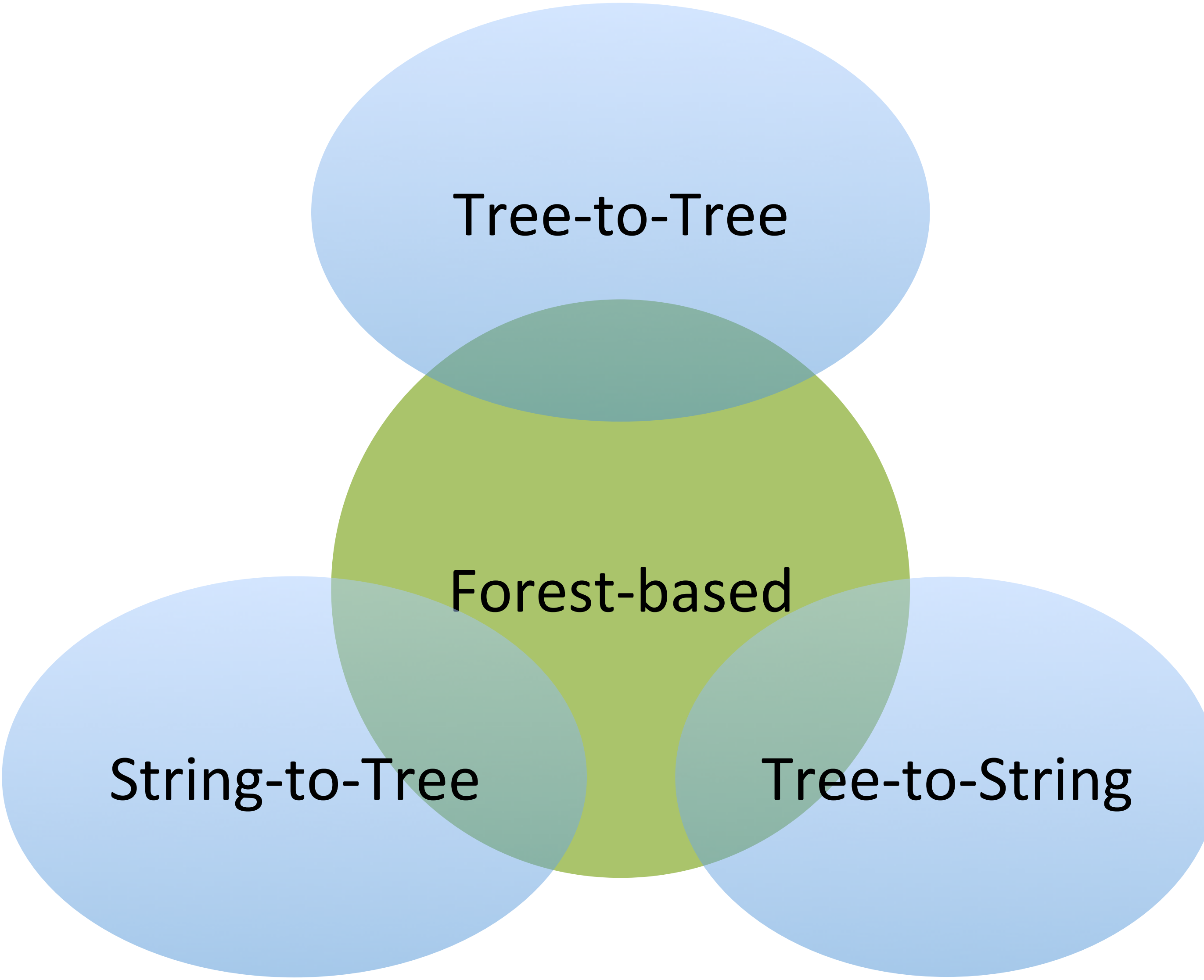
Constituent Syntax-based Model

↓

Dependency Syntax-based Model

# Constituent Syntax-based Models





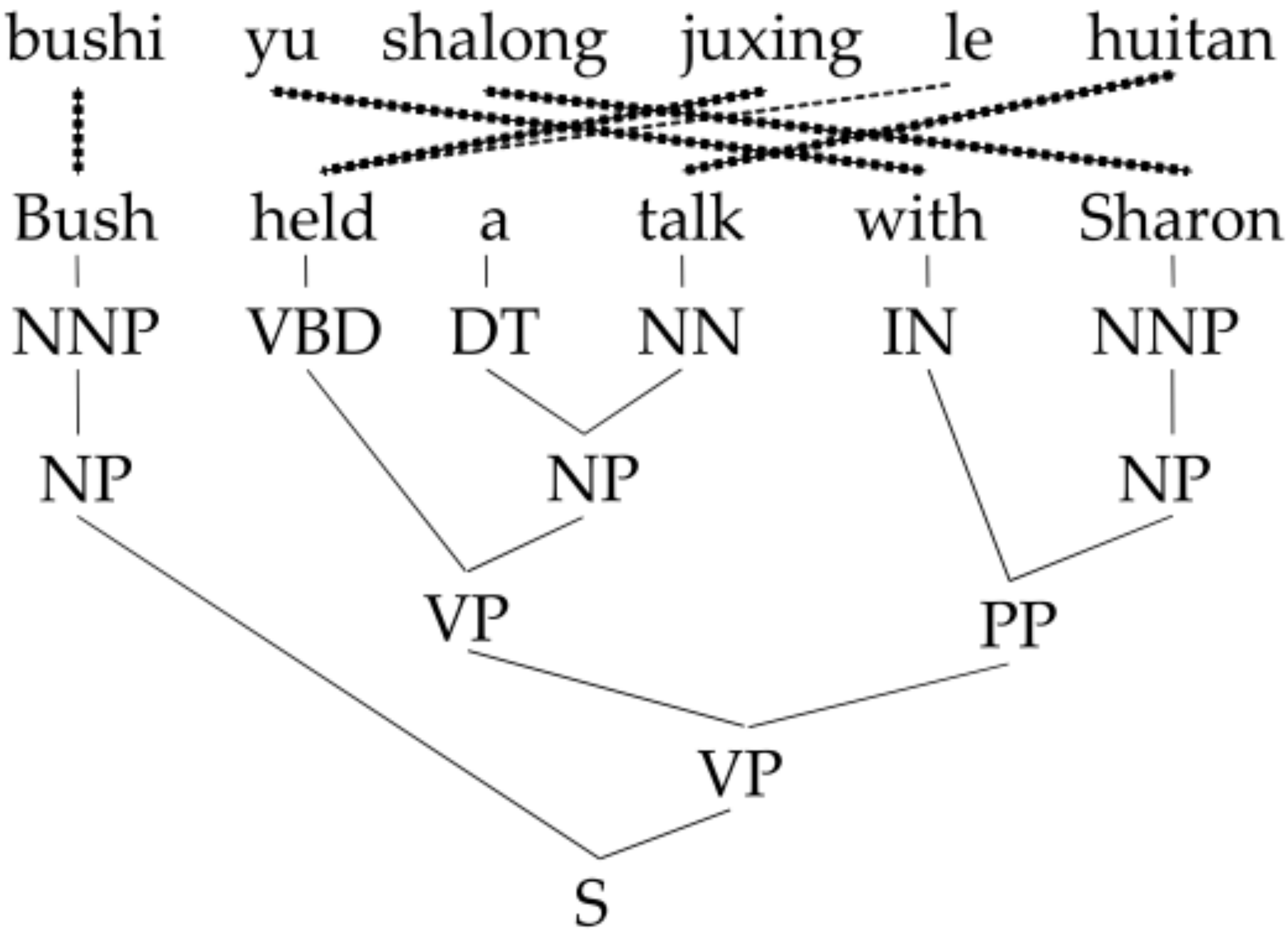
# String-to-Tree Model




- Kenji Yamada and Kevin Knight. 2001. A syntax-based statistical machine translation model. In Proceedings of ACL 2001.
- Daniel Marcu, Wei Wang, Abdessamad Echihabi, and Kevin Knight. 2006. SPMT: Statistical machine translation with syntactified target language phrases. In Proceedings of EMNLP 2006.
- Michel Galley, Jonathan Graehl, Kevin Knight, Daniel Marcu, Steve DeNeefe, Wei Wang, and Ignacio Thayer. 2006. Scalable inference and training of context-rich syntactic translation models. In Proceedings of COLING-ACL 2006.

# String-to-Tree Model





# String-to-Tree Model



| Source | Target | Probability |
|---|---|---|
| juxing le huiang （举行了会谈） | VP(VPD(hold) NP(DT(a) NN(meeting))) | 0.6 |
| | VP(VPD(had) NP(DP(a) NN(meeting))) | 0.3 |
| | VP(VPD(had) NP(DT(a) NN(talk))) | 0.1 |
| $x_1$ huitang （$x_1$会谈） | VP($x_1$:VPD NP(DT(a) NN(meeting))) | 0.8 |
| | VP($x_1$:VPD NP(DT(a) NN(talk))) | 0.2 |
| juxing le $x_1$ （举行了$x_1$） | VP(VPD(hold) NP(DT(a) $x_1$:NN)) | 0.5 |
| | VP(VPD(had) NP(DT(a) $x_1$:NN)) | 0.5 |
| $x_1$ yu $x_2$ （$x_1$与$x_2$） | NP($x_1$:NNP CC(and) $x_2$:NNP)) | 0.9 |

# Tree-to-String Model

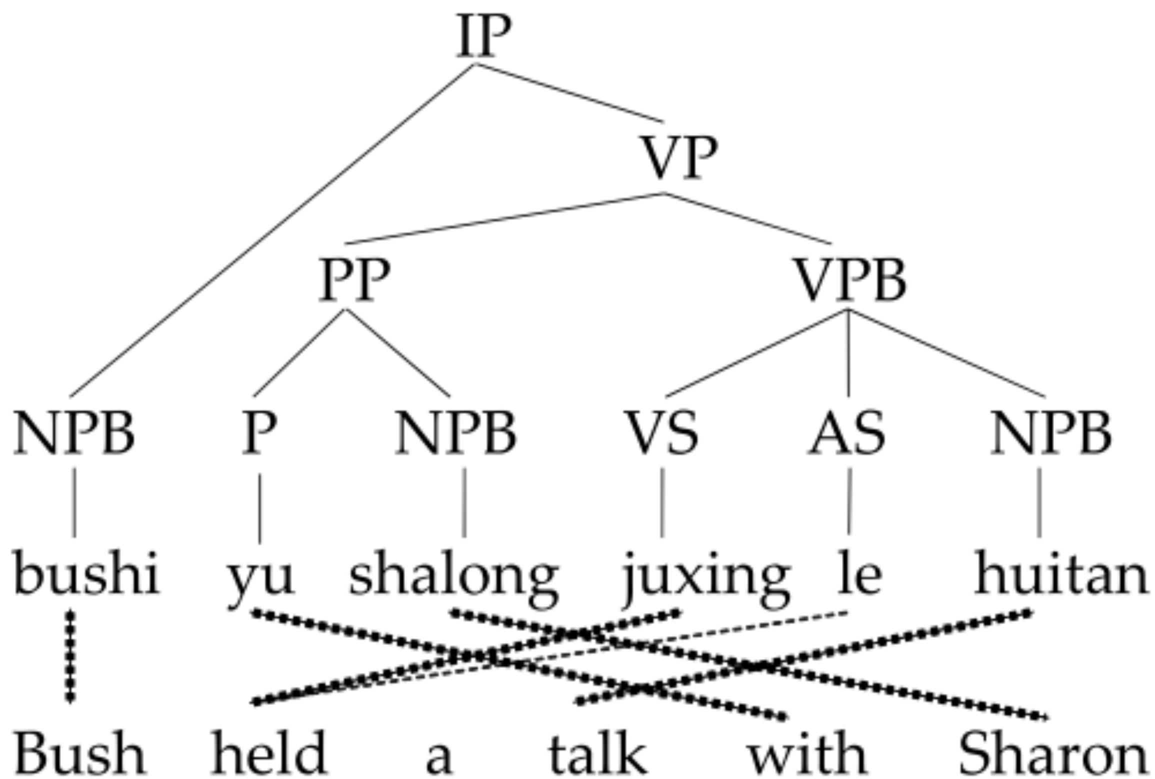


- Yang Liu, Qun Liu, and Shouxun Lin. 2006. Tree-to-String Alignment Template for Statistical Machine Translation. In Proceedings of COLING/ACL 2006, pages 609-616, Sydney, Australia, July.

  (Meritorious Asian NLP Paper Award)
- Huang, Liang, Kevin Knight, and Aravind Joshi. "Statistical syntax-directed translation with extended domain of locality." Proceedings of AMTA. 2006.

# Tree-to-String Model





# Tree-to-String Model



| Source | Target | Probability |
|---|---|---|
| VPB(VS(juxing) AS(le) NPB(huiang)) （举行了会谈） | hold a meeting | 0.6 |
| | have a meeting | 0.3 |
| | have a talk | 0.1 |
| VPB(VS(juxing) AS(le) $x_1$) （举行了$x_1$） | hold a $x_1$ | 0.5 |
| | have a $x_1$ | 0.5 |
| VP(PP(P(yu) $x_1$:NPB) $x_2$:VPB) （与 $x_1$ $x_2$） | $x_2$ with $x_1$ | 0.9 |
| IP($x_1$:NPB VP($x_2$:PP $x_3$:VPB)) | $x_1$ $x_3$ $x_2$ | 0.7 |

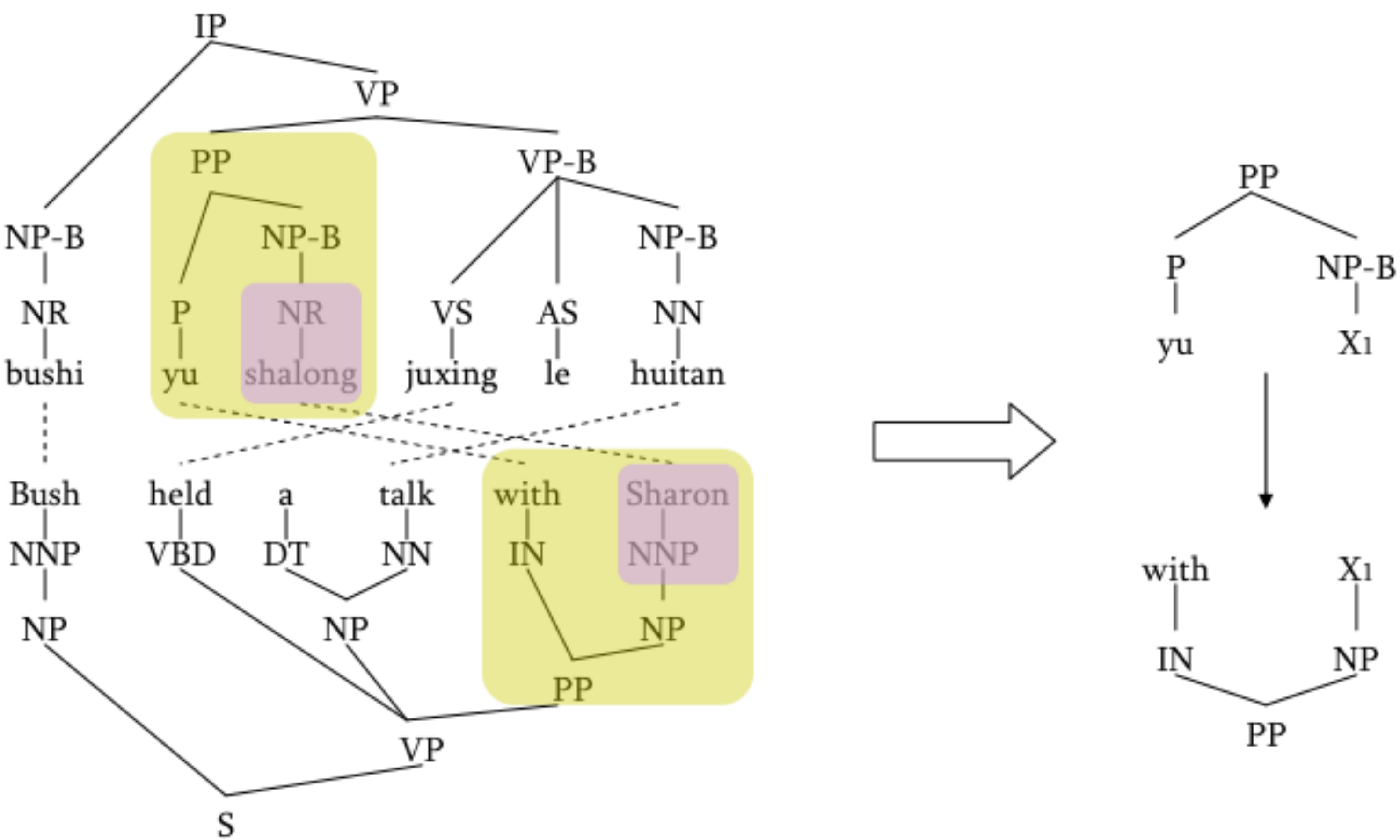
# Tree-to-Tree Model



- Jason Eisner. 2003. Learning non-isomorphic tree mappings for machine translation. In Proc. of ACL 2003
- Min Zhang, Hongfei Jiang, Aiti Aw, Haizhou Li, Chew Lim Tan, and Sheng Li. "A tree sequence alignment-based tree-to-tree translation model." *ACL-08: HLT* (2008): 559.
- Yang Liu, Yajuan Lü, and Qun Liu. 2009. Improving Tree-to-Tree Translation with Packed Forests. In Proceedings of ACL/IJCNLP 2009, pages 558-566, Singapore, August.

# Tree-to-Tree Model





# Constituent Syntax-based Models



Advantage:

- Linguistic knowledge used
  - ➢ Long distance dependency

Disadvantage:

- Ungrammatical phrases
- Syntactic Ambiguity
- Computational Complexity
  - ➢ Synchronous TSG

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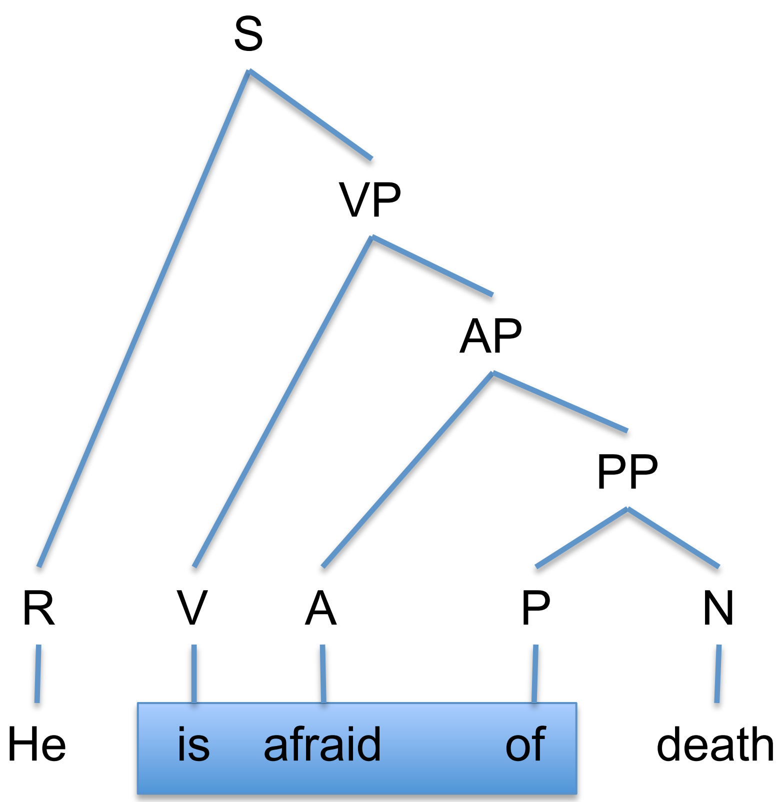
# Ungrammatical Phrases






- Pure tree-based models get very low performance, even lower than phrase-based models
- Various techniques are developed to incorporate ungrammatical phrases into tree-based models, which lead to an significant improvement on tree-based models

# Constituent Syntax-based Models



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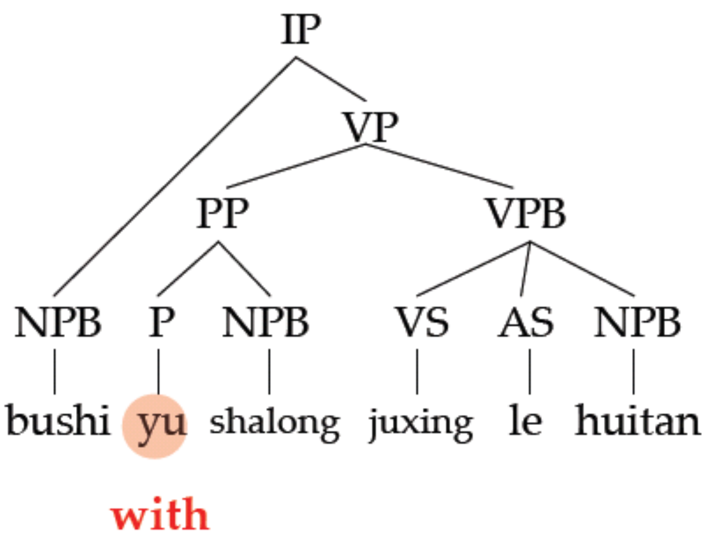
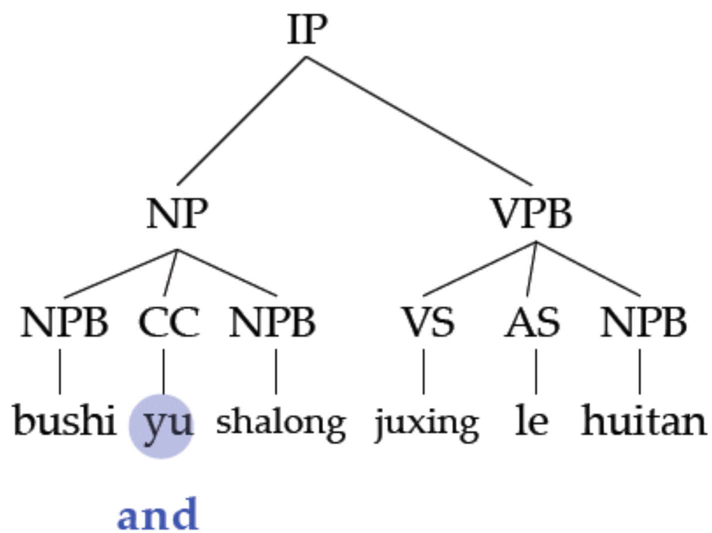
# Syntactic Ambiguity



**It is important to choose a correct tree for producing a good translation!**



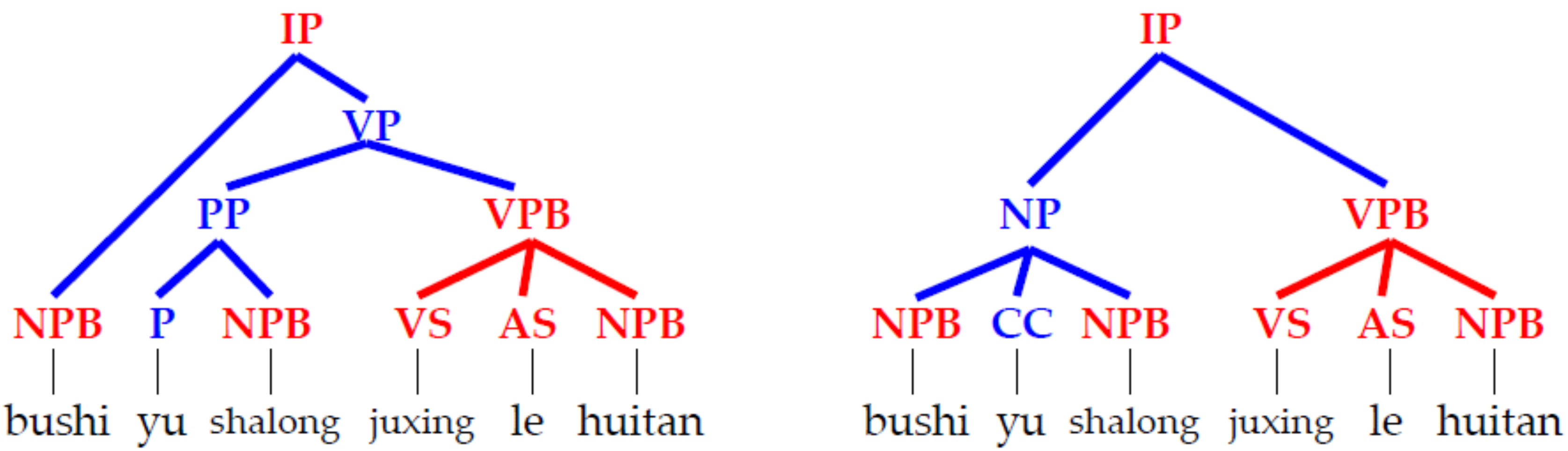




``Bush held a talk with Sharon''

``Bush and Sharon held a talk''

# 1-best → n-best trees?






Very few variations among the *n*-best trees!

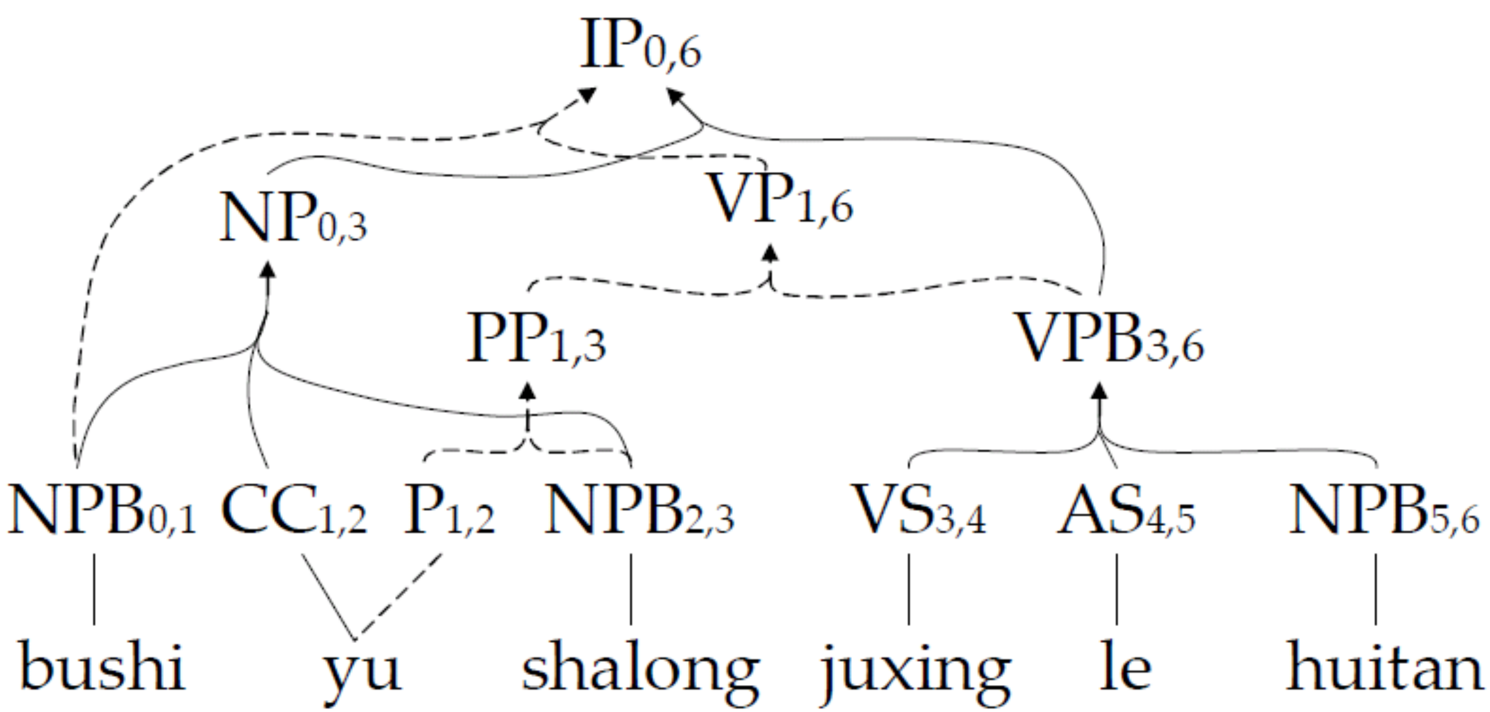
# Forest-based Translation



- Mi, Haitao, Liang Huang, and Qun Liu. "Forest-Based Translation." Proceedings of ACL 2008.
- Mi, Haitao, and Liang Huang. "Forest-based translation rule extraction." Proceedings of the EMNLP 2008.

# Packed Forest





# N-best Trees vs. Forest

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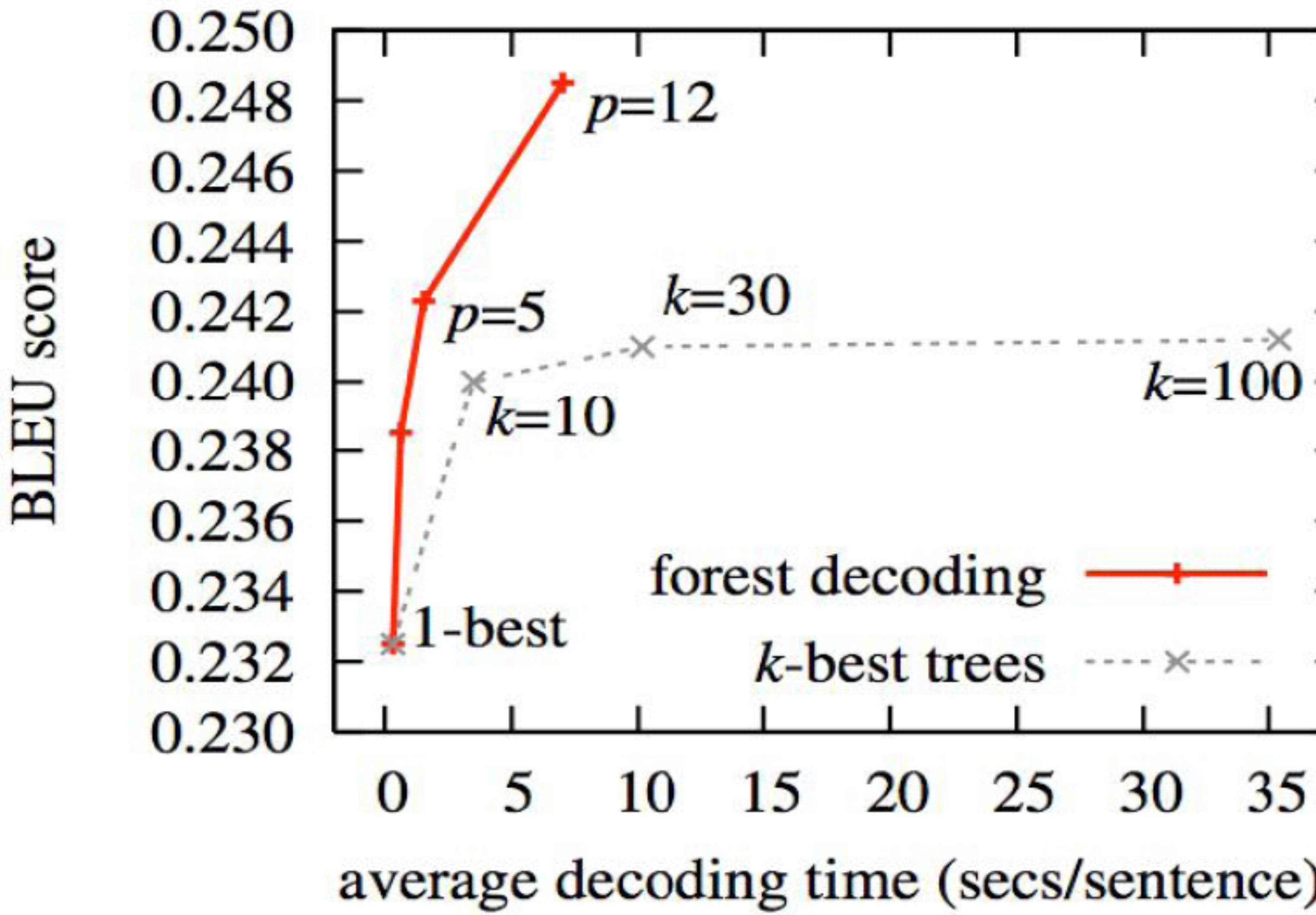

# Constituent Syntax-based Models



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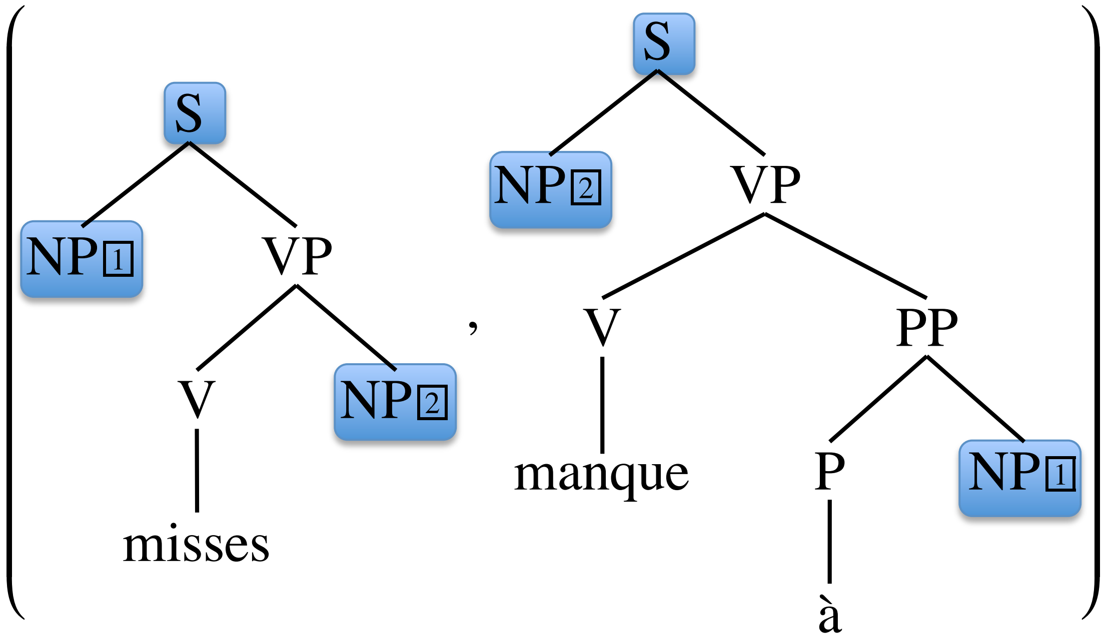
- Computational Complexity
  - ➢ Synchronous TSG

# Synchronous TSG

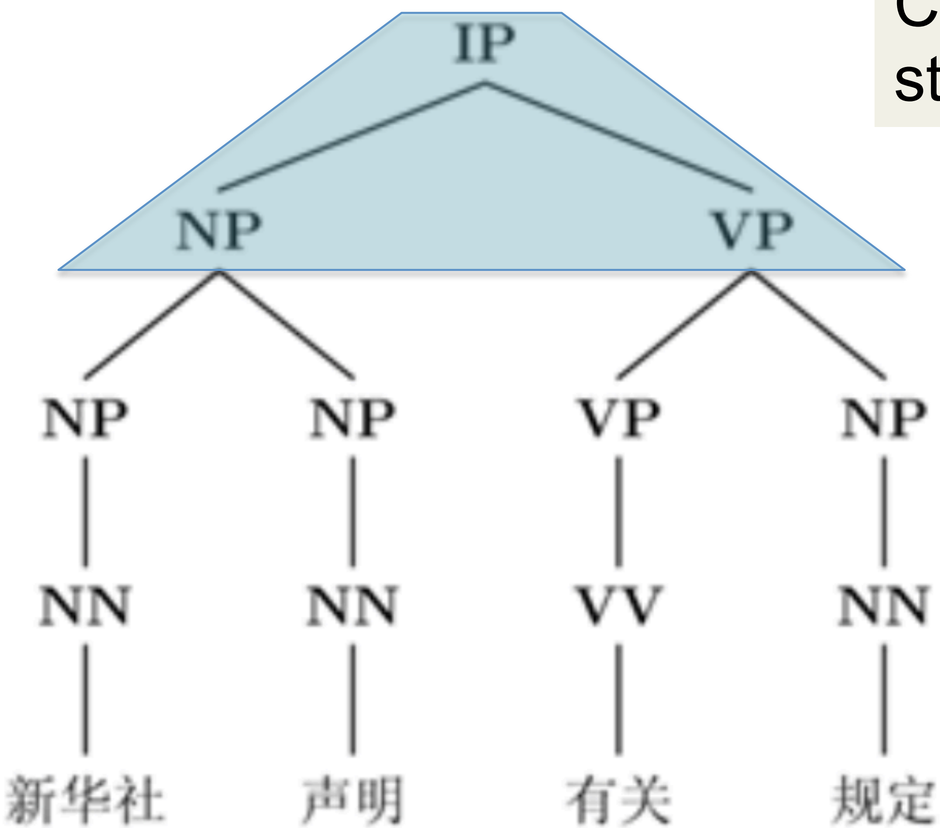





Synchronous CFG can be regarded as a special case of Synchronous TSG where the trees are limited to have only two layers of nodes

# Synchr. TSG vs Synchr. CFG



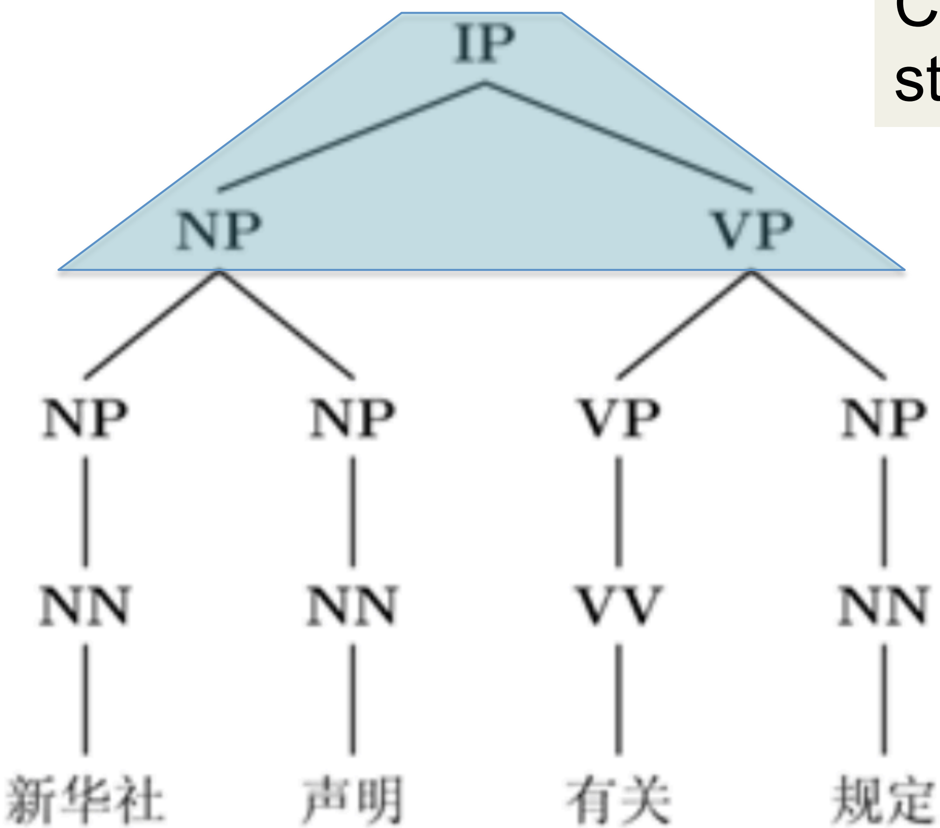



Considering matching a rule starting from the root node

For Synchronous CFG, there is only one possible tree in the source side

# Synchr. TSG vs Synchr. CFG



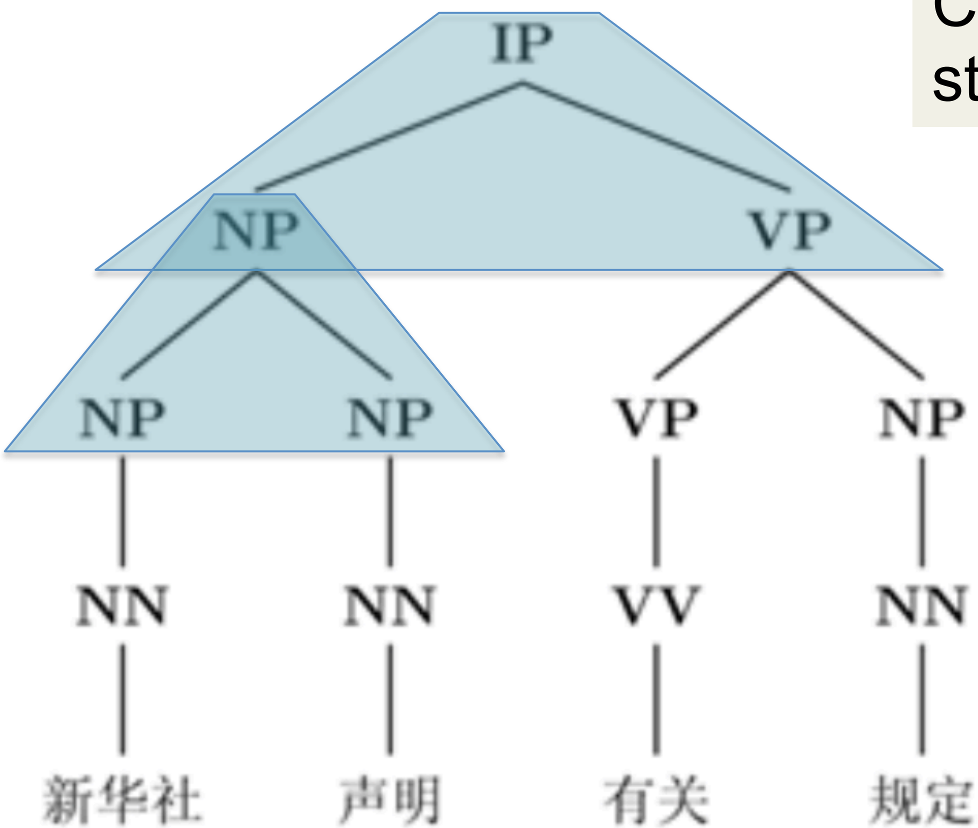



Considering matching a rule starting from the root node

For Synchronous TSG, there are a large number of possible trees in the source side

# Synchr. TSG vs Synchr. CFG



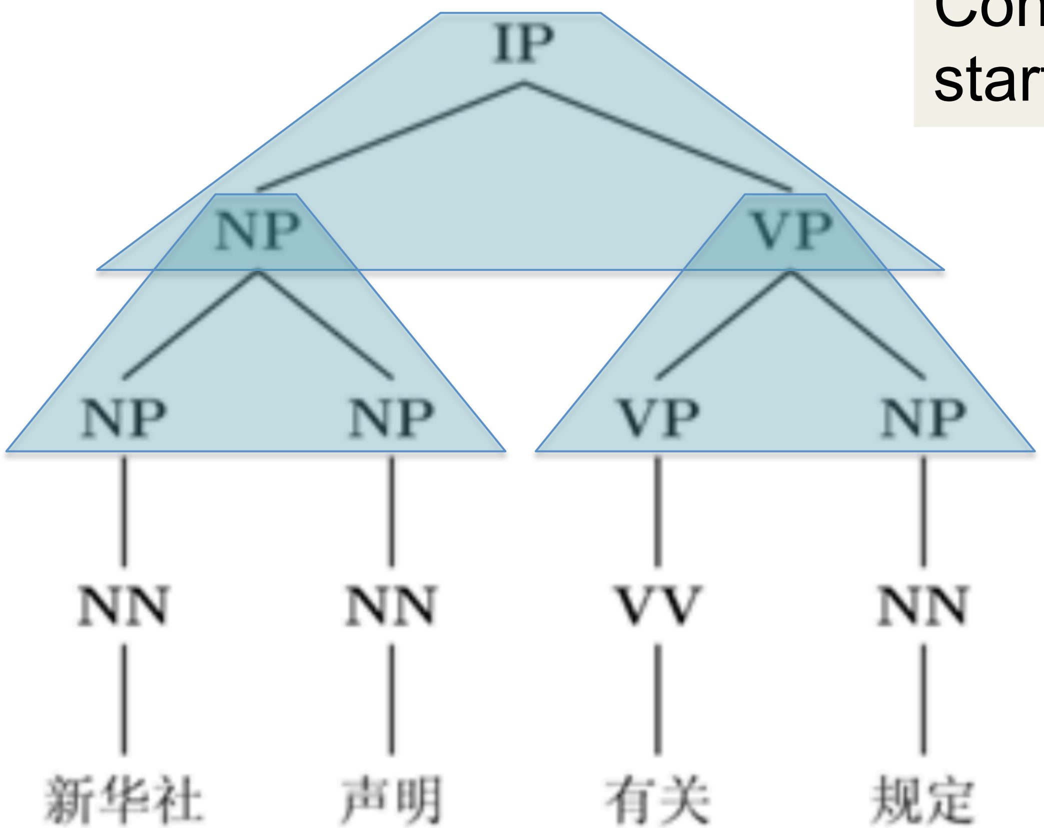



Considering matching a rule starting from the root node

For Synchronous TSG, there are a large number of possible trees in the source side

# Synchr. TSG vs Synchr. CFG



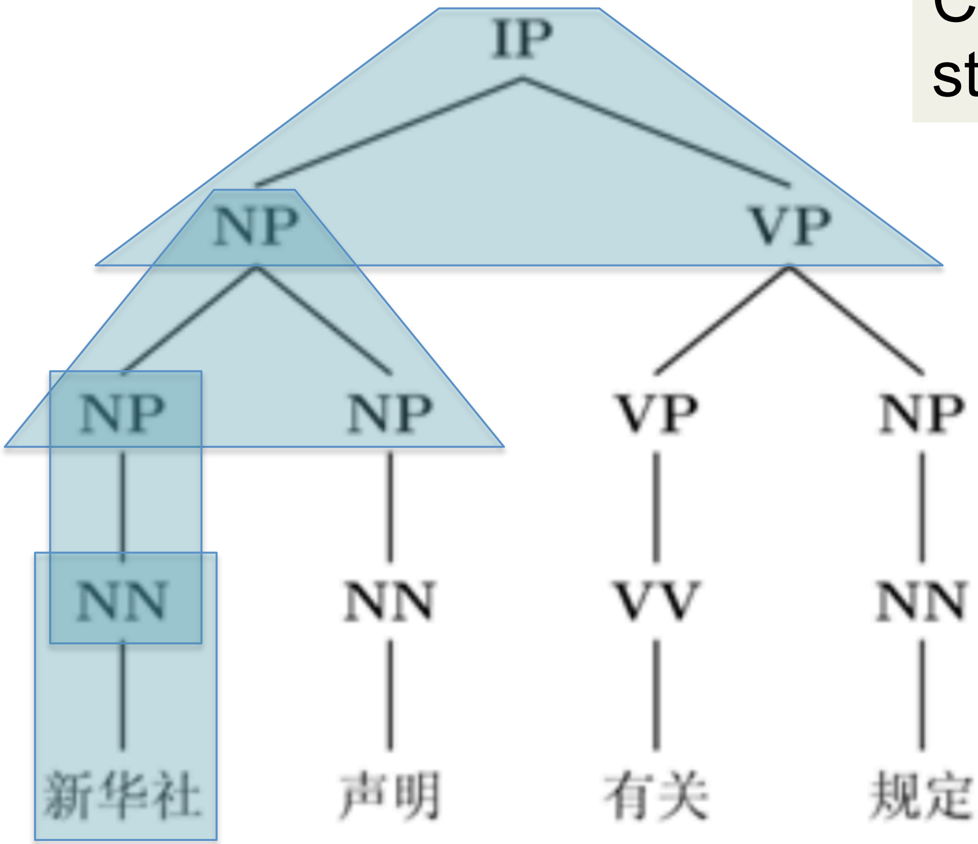



Considering matching a rule starting from the root node

For Synchronous TSG, there are a large number of possible trees in the source side

# Synchr. TSG vs Synchr. CFG



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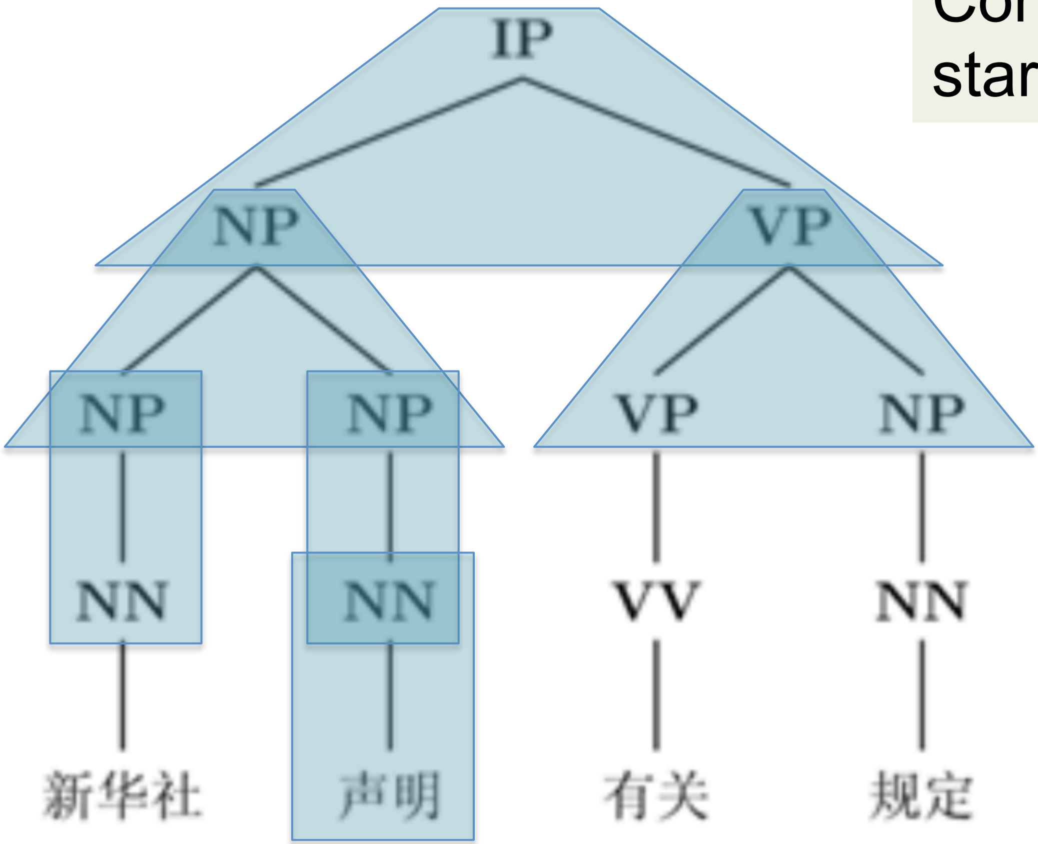
# Synchr. TSG vs Synchr. CFG



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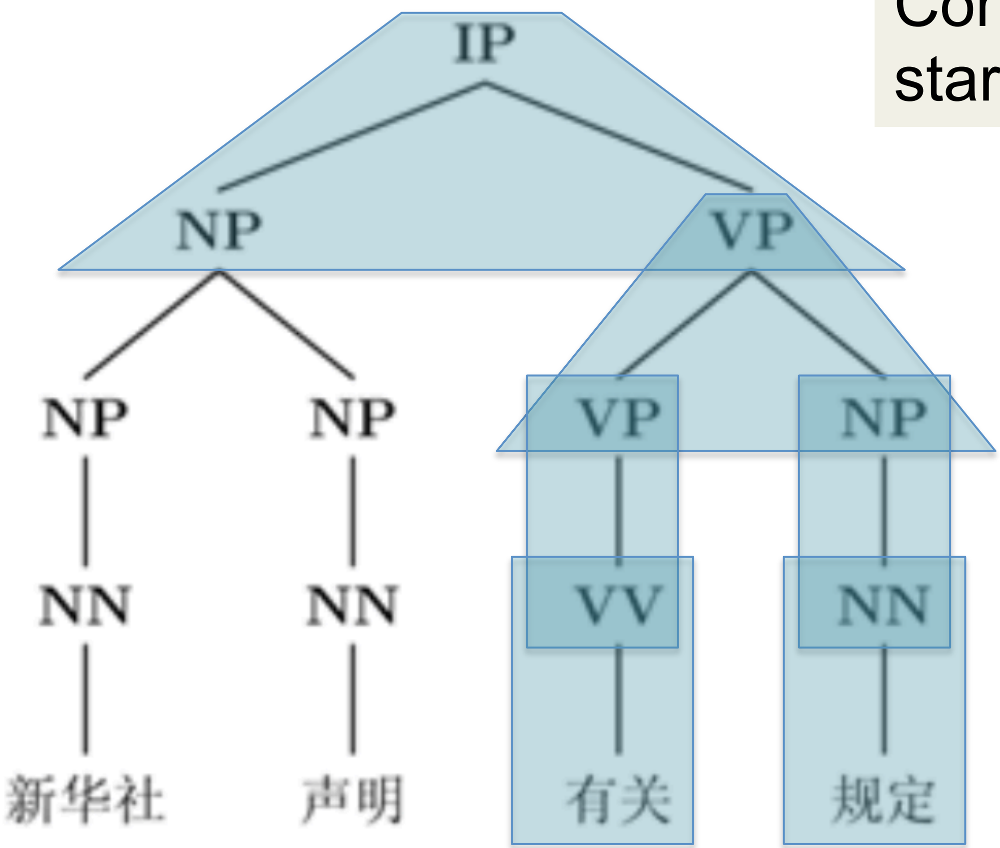
# Synchr. TSG vs Synchr. CFG






Considering matching a rule starting from the root node

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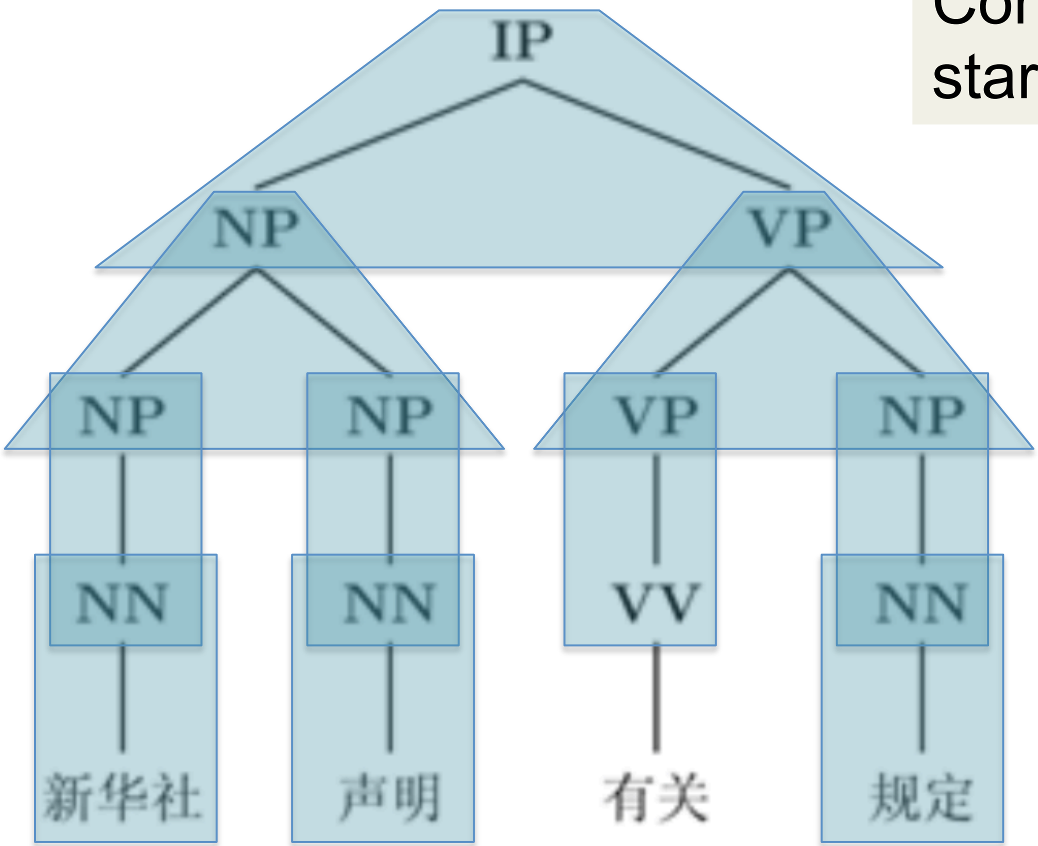
# Synchr. TSG vs Synchr. CFG






Considering matching a rule starting from the root node

For Synchronous TSG, there are a large number of possible trees in the source side

# Synchr. TSG vs Synchr. CFG



- The implementation of Synchronous TSG is much more complex than Synchronous CFG, both in space and in time
- Technologies are developed to deal with the rule indexing problem for Synchronous TSG decoder [Zhang et al., ACL-IJCNLP 2009]
- The syntax based decoder implemented in Moses does not support Synchronous TSG model with rules having more than two layers.

# Constituent Syntax-based Models



Advantage:

- Linguistic knowledge used
  - ➢ Long distance dependency

Disadvantage:

- Ungrammatical phrases
- Syntactic Ambiguity
- Computational Complexity
  - ➢ Synchronous TSG

Is it possible to build a linguistically syntax-based model with the complexity of Synchronous CFG?

# Syntax-based Model



Hierarchical Phrase-based Model

Constituent Syntax-based Model

Dependency Syntax-based Model

# History



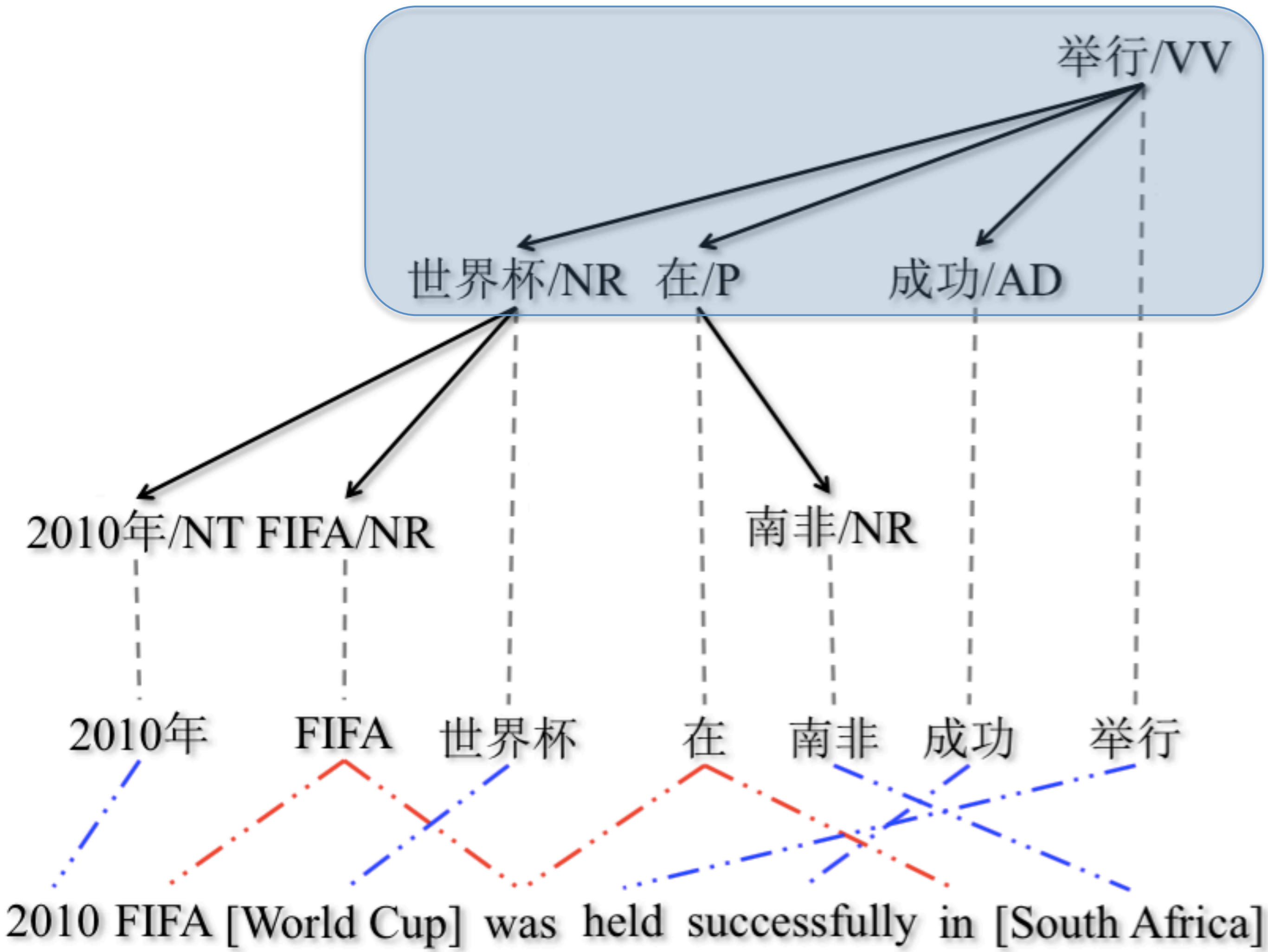
Ding Y. et al. 2003, 2004

Quick C. et al. 2005

Xiong D. et al. 2007

# Difficult of Dependency-based SMT

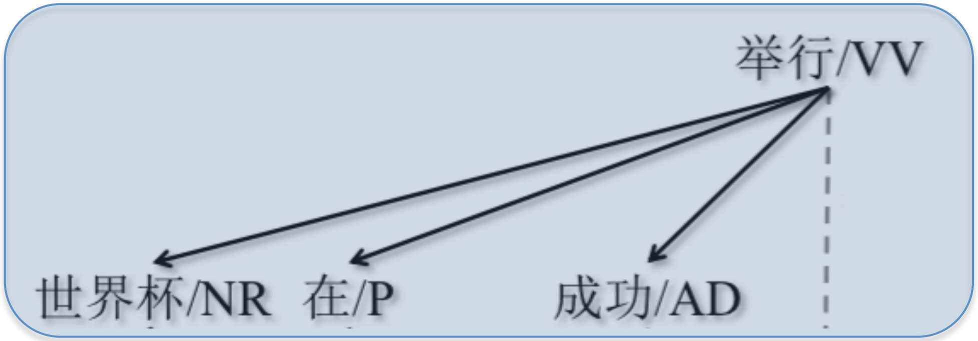




# Difficult of Dependency–based SMT



A dependency translation rule:




…世界杯(World Cup)…在(in)…成功(Successfully) 举行(was held)

Problem: Low Coverage，Sparcity

# History



Ding Y. et al. 2003, 2004

Quick C. et al. 2005

Xiong D. et al. 2007

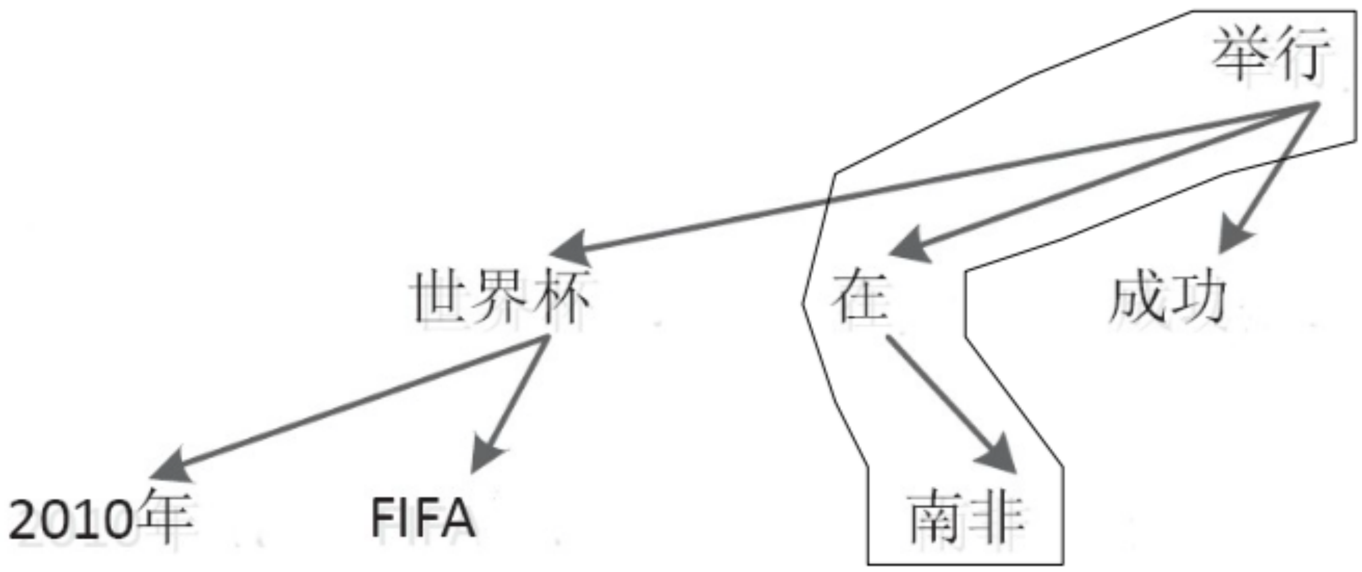
Dependency-Treelet-based Approach

# Dependency-Treelet-based Approach



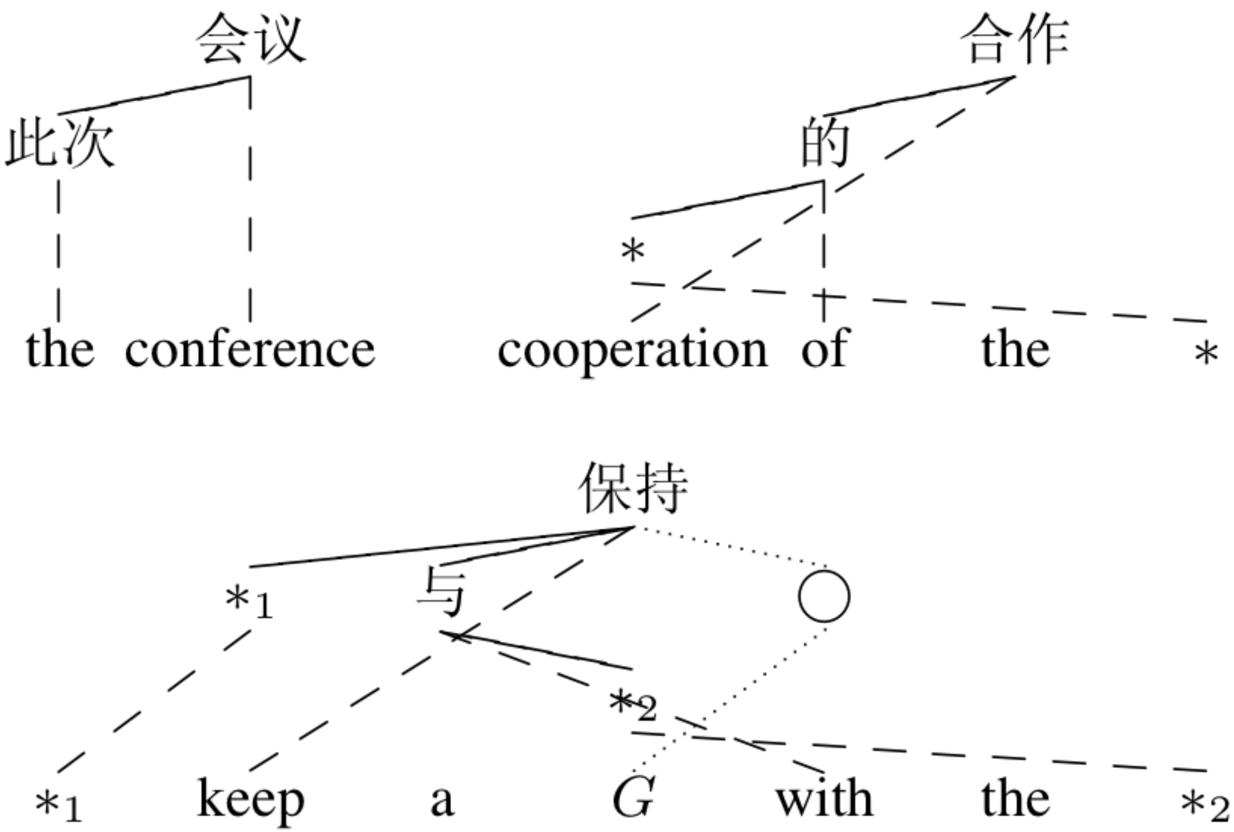
Dependency Treelet:

Any connected subgraph of a dependency tree



# Dependency-Treelet-based Rules





# Problem of Dep-Treelet-based Approach



- The partition of a dependency tree to a set of treelets is too flexible (more flexible than the partition of a constituent tree in a tree-to-string model)
- The reordering is difficult in target side:
  - These are no sequential orders between treelets
  - The translation of a treelet is usually non-continuous

# Dependency-to-String Model

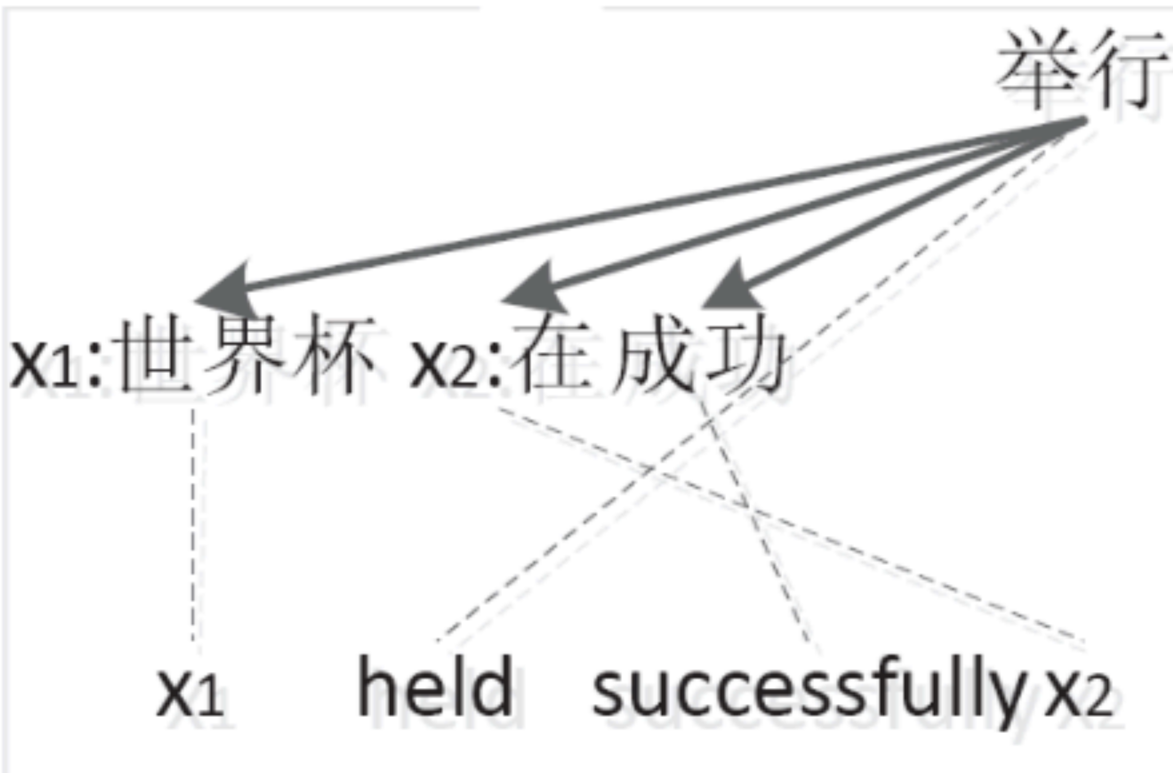


- Our Solution
  - One layer subtree (head-dependency）
  - Using POS for Smoothing

Jun Xie, Haitao Mi and Qun Liu, A novel dependency-to-string model for statistical machine translation, in the Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP2011), pages 216-226, Edinburgh, Scotland, UK. July 27–31, 2011

# Dep-to-String Rule



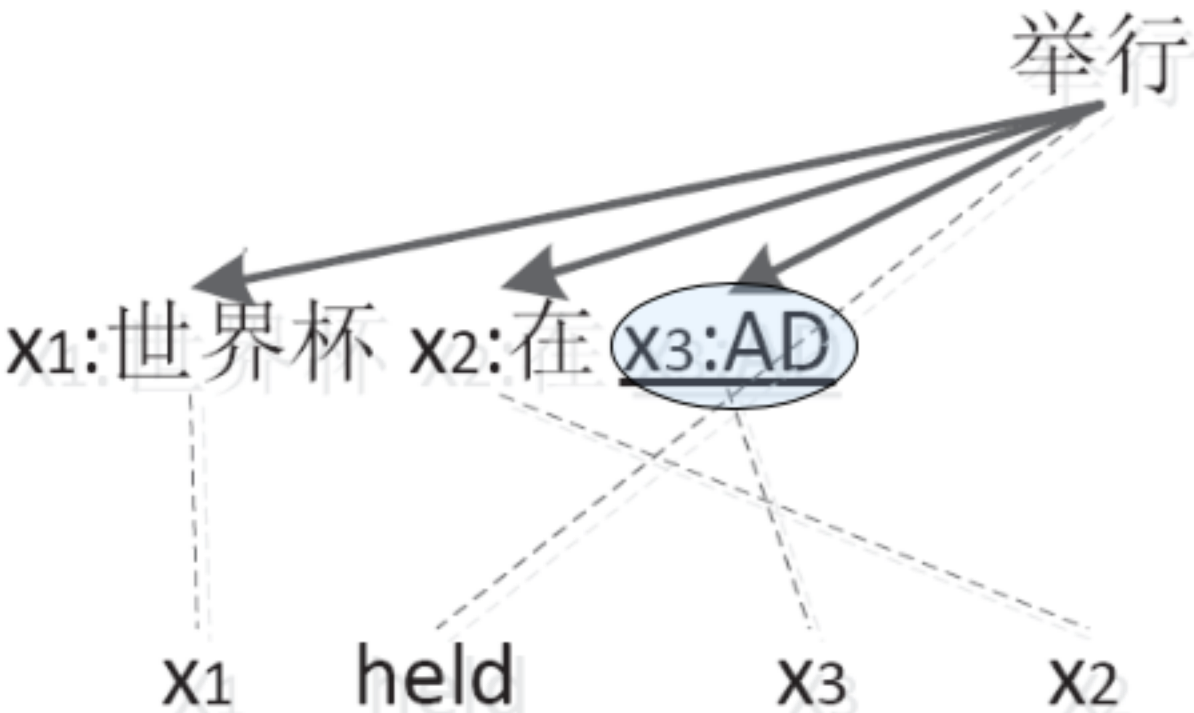



($x_1$:世界杯)($x_2$:在)(成功) 举行

$\rightarrow$ $x_1$ held successfully $x_2$

# Smoothing with：Leaf nodes



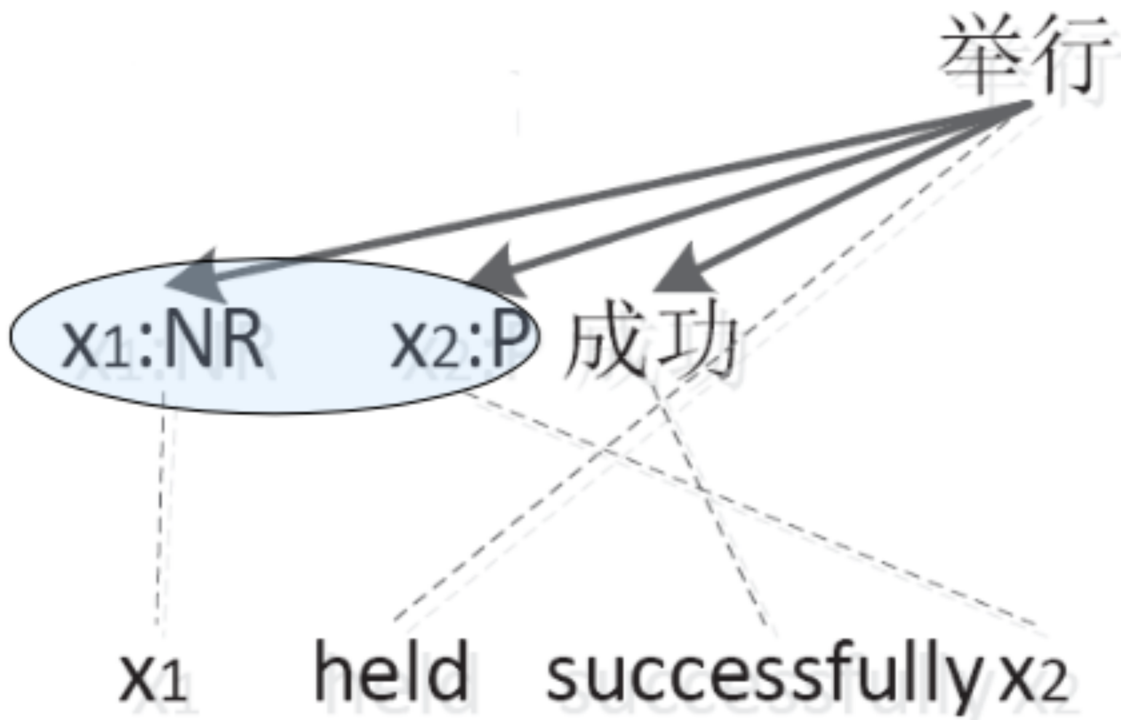



($x_1$:世界杯)($x_2$:在)($x_3$:AD) 举行

→ $x_1$ held $x_3$ $x_2$

# Smoothing with：Internal nodes



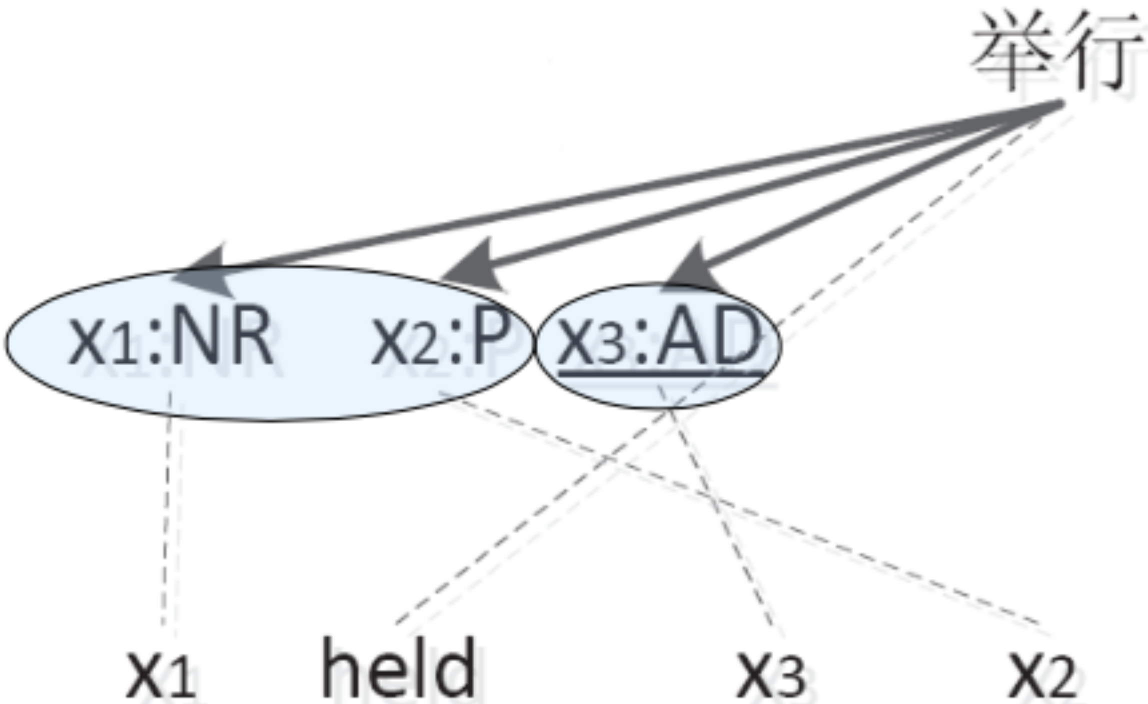



$(x_1{:}NR)(x_2{:}P)$(成功) 举行

$\rightarrow$ $x_1$ held successfully $x_2$

# Smoothing with: Leaf & Internal node

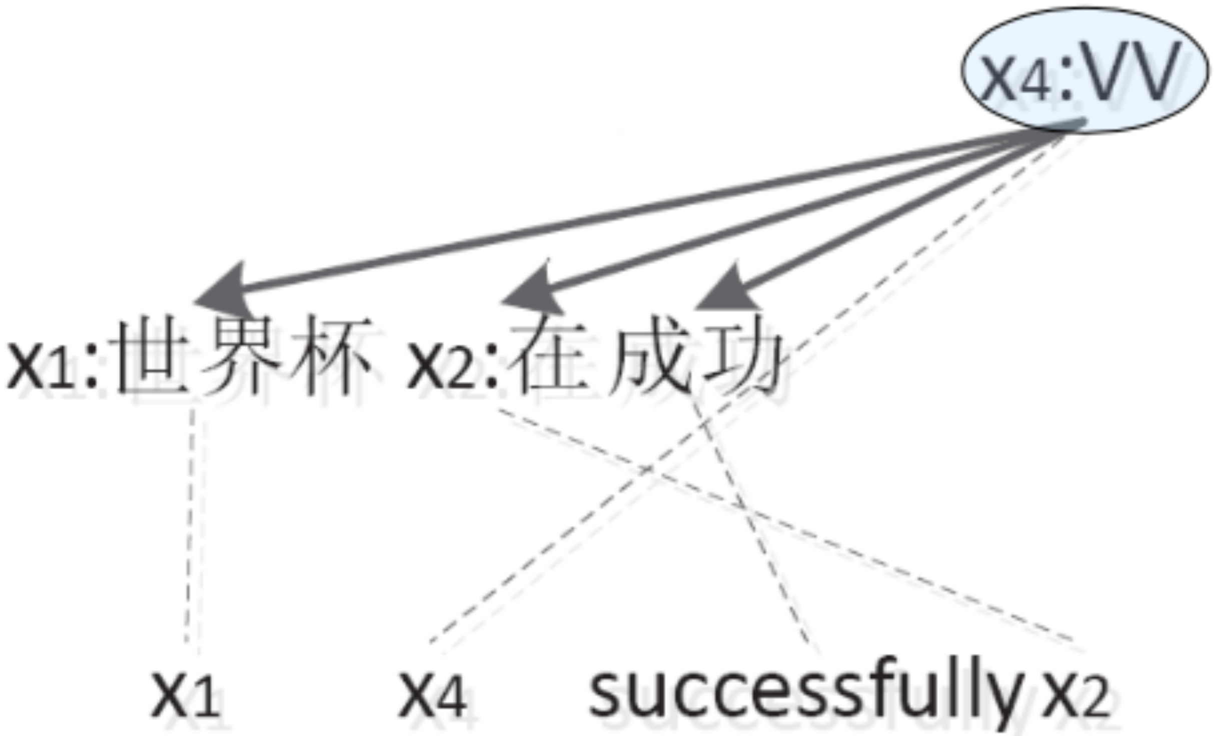





(x1:NR)(x2:P)(<u>x3:AD</u>) 举行
→ x1 held x3 x2

# Smoothing with：Head node



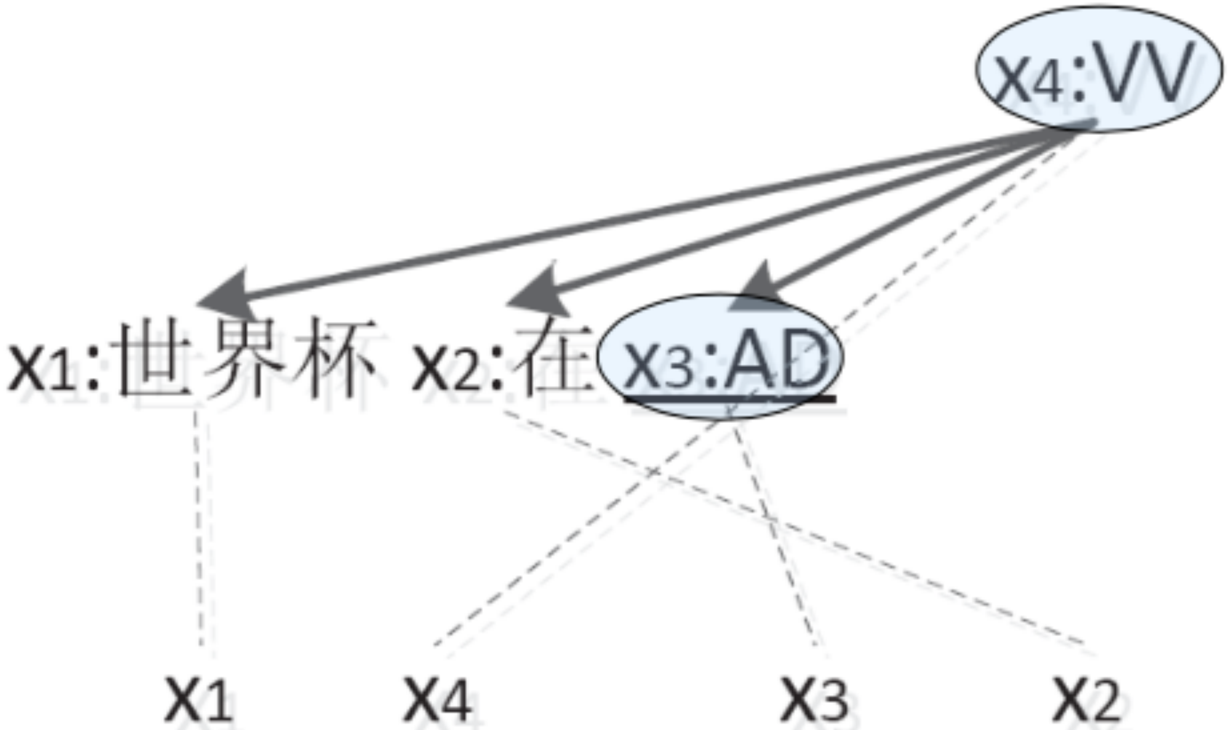



($x_1$:世界杯)($x_2$:在)(成功) $x_4$:VV

$\rightarrow$ $x_1$ $x_4$ successfully $x_2$

# Smoothing with：Head & Leaf nodes

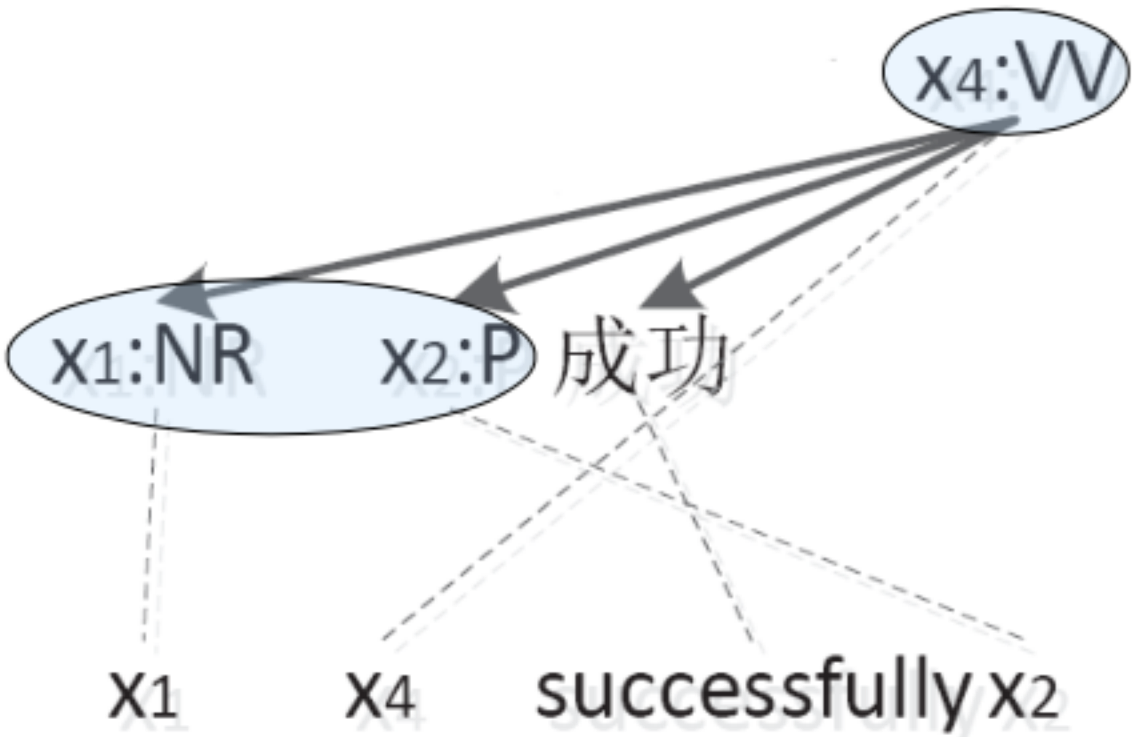
www.adaptcentre.ie




(x1:世界杯)(x2:在)(x3:AD) x4:VV
→ X1 X4 X3 X2

# Smoothing with： Head & Internal nodes



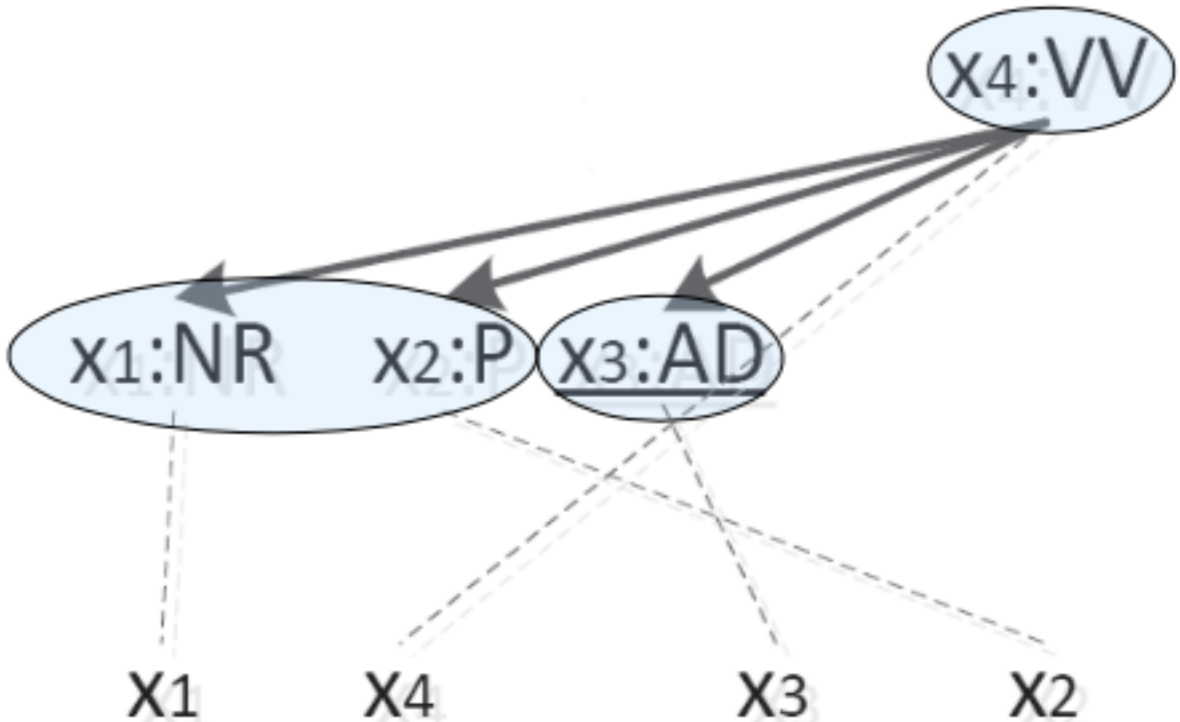



(x1:NR)(x2:P)(成功) x4:VV

→ x1 x4 successfully x2

# Smoothing with： All nodes






($x_1$:NR)($x_2$:P)($\underline{x_3\text{:AD}}$) $x_4$:VV

$\rightarrow$ $x_1$ $x_4$ $x_3$ $x_2$

# Experiments



| System | Rule # | MT04(%) | MT05(%) |
|---|---|---|---|
| cons2str | 30M | 34.55 | 31.94 |
| hiero-re | 148M | 35.29 | 33.22 |
| dep2str | 56M | **35.82**$^{+}$ | **33.62**$^{+}$ |

# Dependency-to-String Model



Advantage:

- Linguistic knowledge used
  - Long distance dependency
- Computational Complexity
  - Equivalent to: Synchronous CFG

Disadvantage:

- Ungrammatical phrases
- Syntactic Ambiguity

# Dependency-to-String Model implemented as Synchronous CFG



Liangyou Li, Jun Xie, Andy Way, Qun Liu, Transformation and Decomposition for Efficiently Implementing and Improving Dependency-to-String Model In Moses, In Proceedings of SSST-8, Eighth Workshop on Syntax, Semantics and Structure in Statistical Translation. Pages 122-131. Doha, Qatar. 2014.

- Implement Dependency-to-String in a Synchronous CFG which is compatible with Moses chart decoder
  - Open Source Tools: dep2str
- Implement pseudo-forest to support partially matched head-dependency structures

# Summary: Syntax-based Models

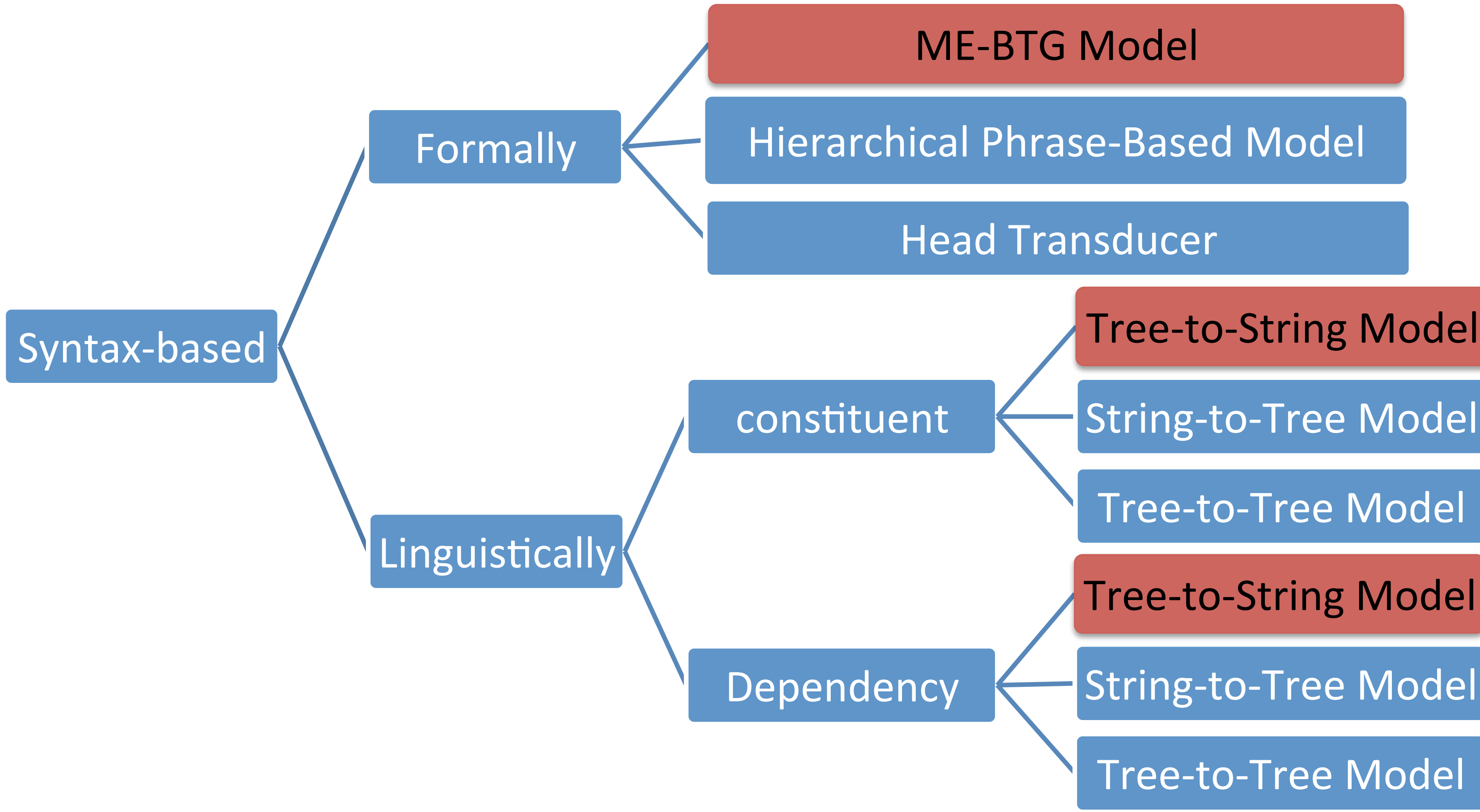


- Syntax-based
  - Formally
    - ME-BTG Model
    - Hierarchical Phrase-Based Model
    - Head Transducer
  - Linguistically
    - constituent
      - Tree-to-String Model
      - String-to-Tree Model
      - Tree-to-Tree Model
    - Dependency
      - Tree-to-String Model
      - String-to-Tree Model
      - Tree-to-Tree Model

# Summary: Syntax-based Models



Our Contribution:



# Overview of Syntax in SMT

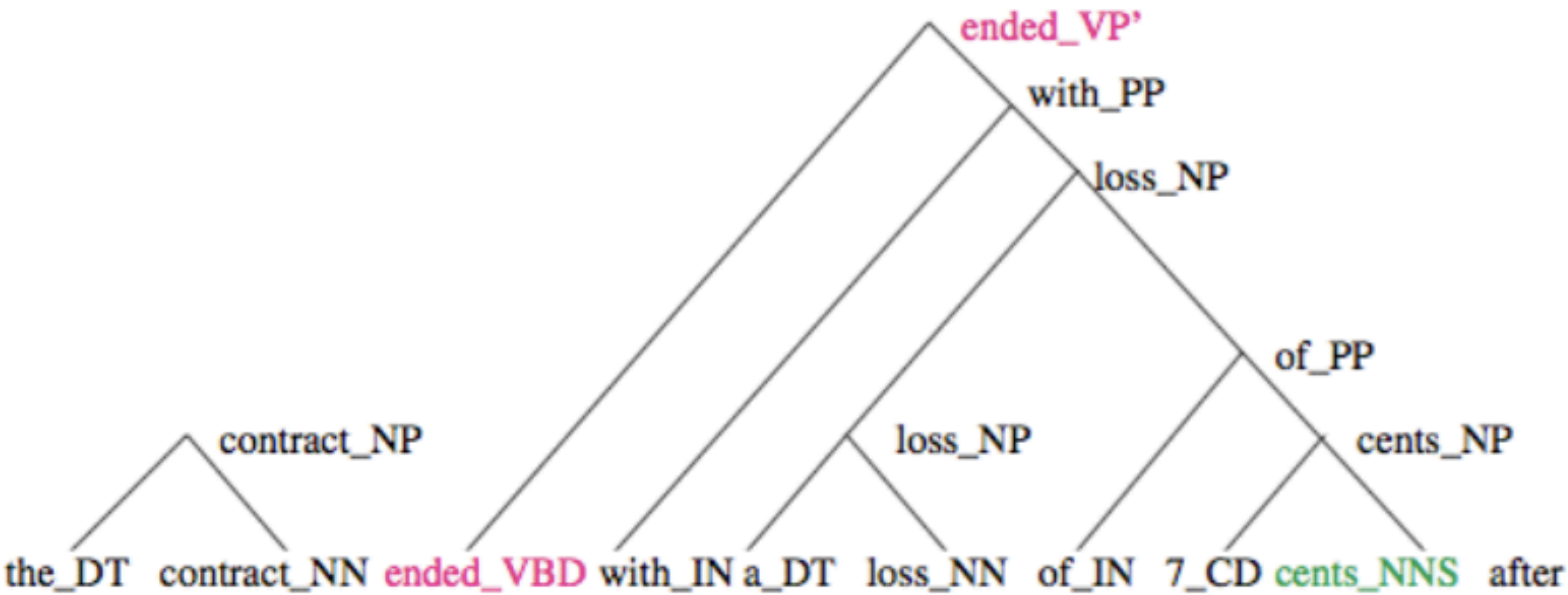


- Introduction
- Syntax-based Translation Models
- **Syntax-based Language Models**
- Syntax-based Translation Evaluations
- Conclusion and Future Work

# Structural Language Model



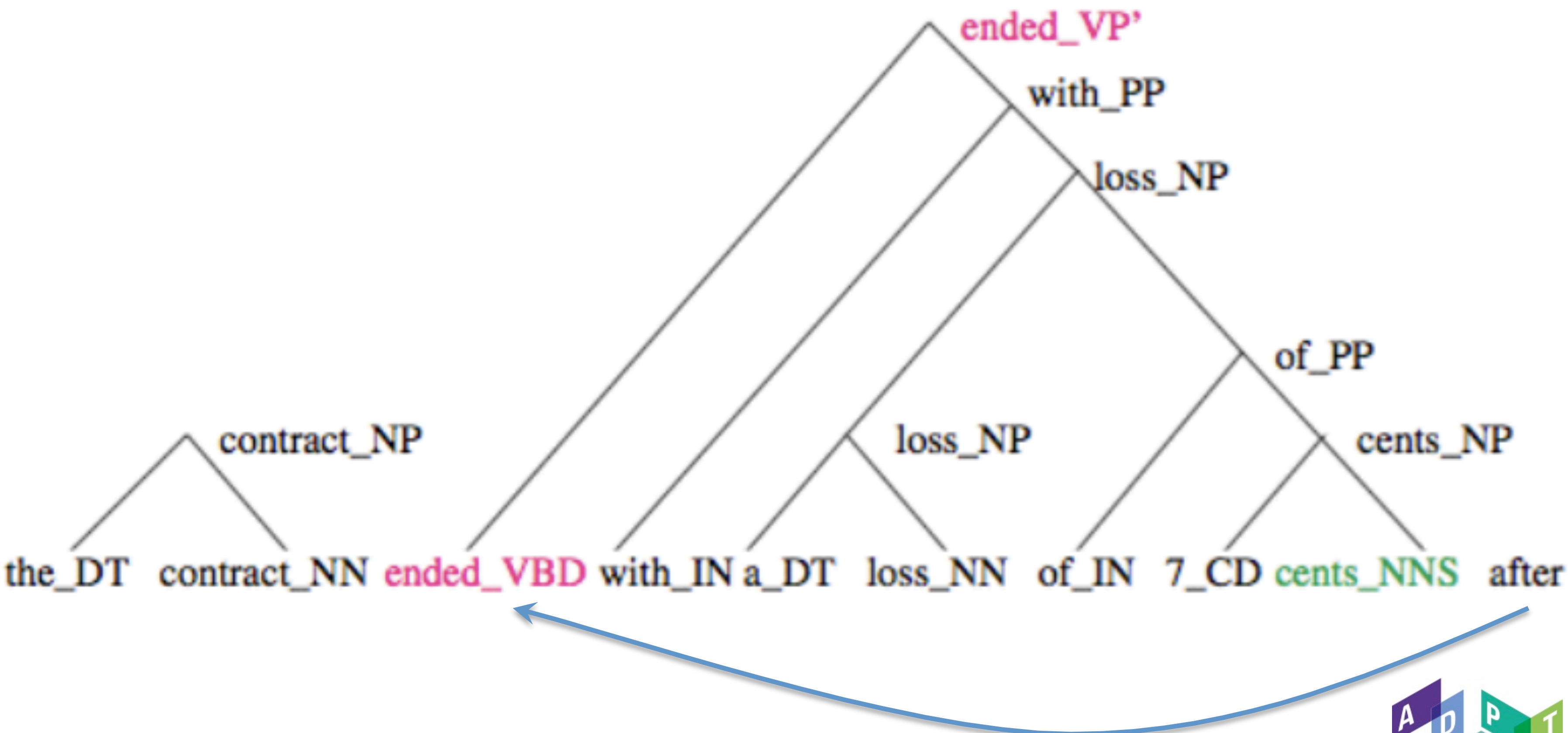
Using syntax information to capture long distance dependency in target side



# Structural Language Model



Using syntax information to capture long distance dependency in target side



# Existing work



- Generative Structural Language Model (Charniak, 2003)

  Eugene Charniak, Kevin Knight, and Kenji Yamada. 2003. Syntax-based language models for statistical machine translation. In *Proceedings of MT Summit IX. Intl. Assoc. for Machine Translation*.
- Idea
  - Estimate head n-gram probability
  - Using POS for smoothing
- Disadvantage
  - Only available when the target tree is generated
  - Can only be used in re-ranking rather than decoding
  - Generative model: features are fixed and not tunable

# Our work



Heng Yu, Haitao Mi, Liang Huang, and Qun Liu. 2014. A Structured Language Model For Incremental Tree-to-String Translation. To be appeared in Proceedings of the 25th International Conference on Computational Linguistics (Coling2014)

- Dependency-based Language Model
- Incremental: can be used in left-to-right decoding
- Discriminative Model:
  - Large number of used-defined features
  - Feature weights tunable

# Preliminary work



- Incremental Tree-to-String Decoding

  Liang Huang and Haitao Mi. 2010. Efficient incremental decoding for tree-to-string translation. In Proceedings of EMNLP, pages 273–283.
- Structured perceptron with inexact search

  Liang Huang, Suphan Fayong, and Yang Guo. 2012. Structured perceptron with inexact search. In Proceedings of NAACL 2012, Montreal, Quebec.

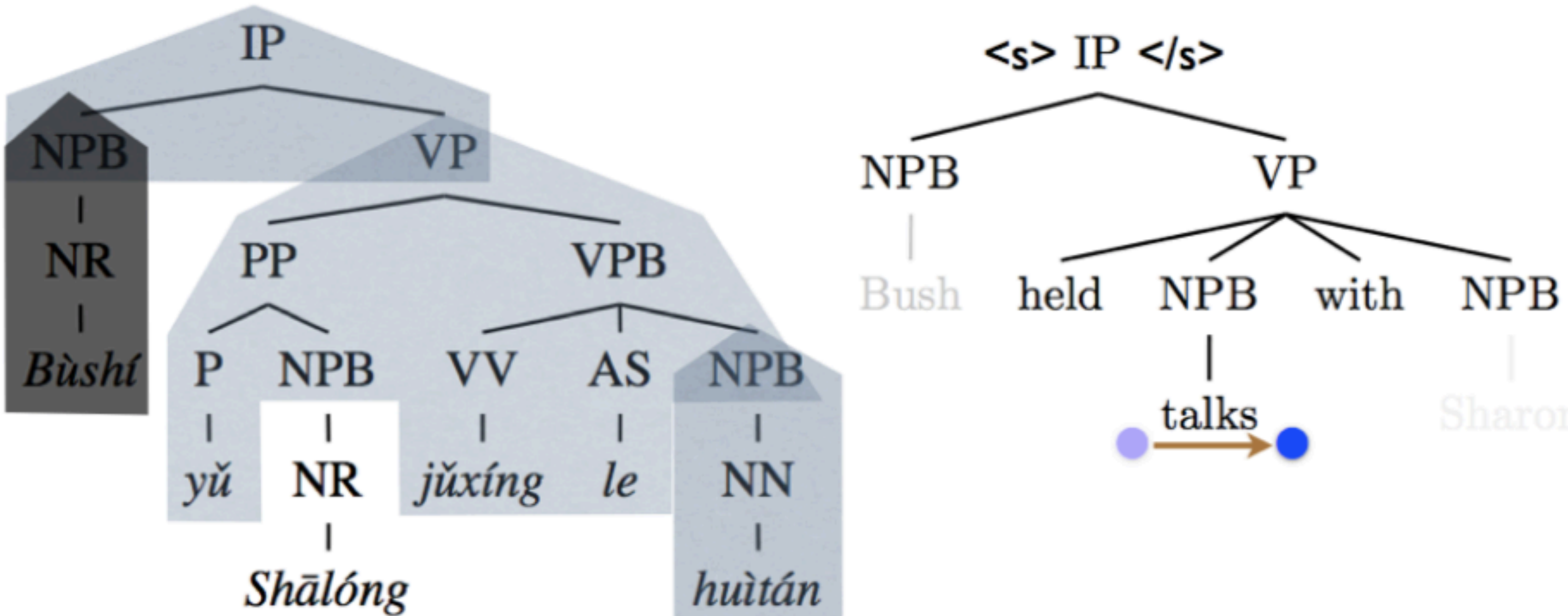
# Incremental Tree-to-String Decoding



Huang 2010

[ε→<s> •IP </s>] [IP→ NPB•VP] [VP →held•NPB with NPB] [NPB→talks• ]

<s> Bush held talks




*action:* scan

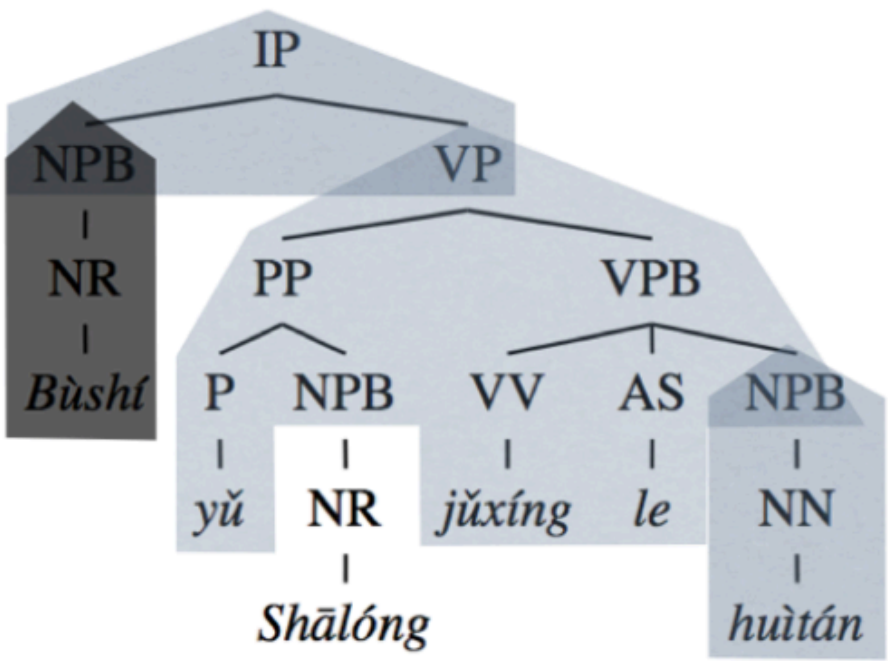
# Incremental Tree-to-String Decoding

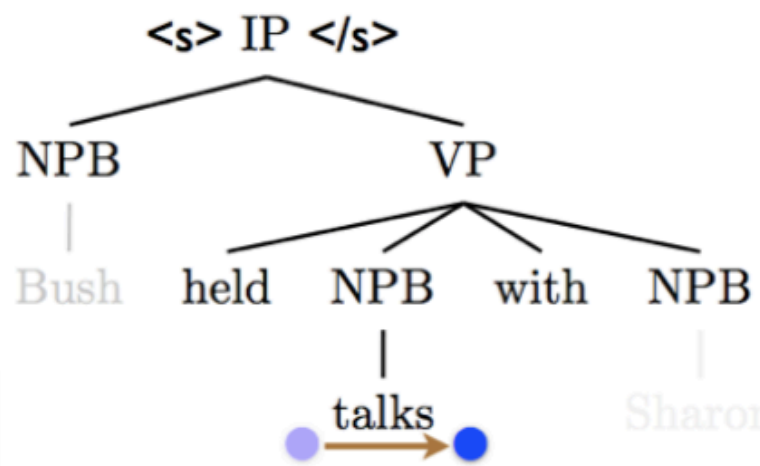


Huang 2010

[ε→<s> .IP </s>] [IP→ NPB.VP] [VP →held.NPB with NPB] [NPB→talks. ]

<s> Bush held talks




*action:* scan

Left-to-Right vs Top-down or Bottom-up

# Online Structural LM for SMT



| | stack | 2-gram | SLM |
|---|---|---|---|
| | [ . IP ] | | |
| *p* | [ . IP ] [. NP VP] | | |
| *p* | [ . IP ] [. NP VP] [. Bush] | | |
| *s* | [ . IP ] [. NP VP] [Bush . ] | Bush | $S_1$: Bush |
| *c* | [ . IP ] [NP . VP] | Bush | $S_1$: |
| *p* | [ . IP ] [NP . VP] [. held NPB with NPB] | Bush | $S_1$: |
| *s* | [ . IP ] [NP . VP] [held . NPB with NPB] | Bush held | $S_2$: Bush held |
| *p, s* | [ . IP ] [NP . VP] [held . NPB with NPB] [a meeting . ] | a meeting | $S_3$: Bush held a meeting |
| *s* | [ . IP ] [NP . VP] [held NP with . NPB] | meeting with | $S_4$: Bush held a meeting with |
| | | | $S'_4$: Bush held a meeting with |
| *p, s* | [ . IP ] [NP . VP] [held NPB with . NPB] [Sharon. ] | with Sharon | $S_5$: Bush held a meeting with Sharon |
| *c* | [ . IP ] [NP . VP] [held NPB with NPB. ] | with Sharon | $S_5$ |
| *c* | [ . IP ] [NP VP. ] | with Sharon | $S_5$ |
| *c* | [ IP . ] | with Sharon | $S_5$ |

# Experiment Results



| System | BLEU | (sec/sen) |
|---|---|---|
| baseline (BL) | 21.06 | 5.7 |
| BL + reranking | 21.23 | 0.03 |
| BL + PTB $n$-gram | 21.10 | 6.3 |
| BL + Hassan | 21.30 | 8.4 |
| BL + ours | 21.64* | 48.0 |

| System | 03 | 04 | 05 | 08 |
|---|---|---|---|---|
| baseline | 19.94 | 22.03 | 19.92 | 21.06 |
| +SLM | 21.49* | 22.33 | 20.51* | 21.64* |

Training Corpus:

1.5M sent. pairs

Decoding time:

8 x Baseline

# Overview of Syntax in SMT



- Introduction
- Syntax-based Translation Models
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- **Syntax-based Translation Evaluations**
- Conclusion and Future Work

# Evaluation for Machine Translation



Candidate 1: It is a guide to action which ensures that the military always obeys the command of the party

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct

Reference 1: It is a guide to action that ensures that the military will forever heed party commands

Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the party

Reference 3: It is the practical guide for the army to heed the directions of the party

Question: Given the human translations as references, how to evaluation the machine translation candidates automatically?

# Existing MT Evaluation Metrics



- Lexicalized Metrics

  BLEU NIST Rouge WER PER METEOR AMBER
- Syntax-based Metrics

  STM HWCM
- Semantic-based Metrics

  MEANT HMEANT
- Combinational Metrics

  LAYERED DISCOTK

# Existing MT Evaluation Metrics



| Metrics | 知识类型 | 模型 | 优点 | 缺点 |
|---|---|---|---|---|
| 基于词汇的方法 | 词汇 | 相似度错误率 | 善于捕捉词汇或短语 | 不能捕捉句法结构 |
| 基于句法的方法 | 句法信息 | 相似度 | 一定程度上捕捉句法信息 | 机器译文端句法分析正确率不能保证 |
| 基于语义的方法 | 语义信息 | 相似度 | 一定程度上捕捉语义信息 | SRL准确率不理想缺乏有效的语义表示方法 |
| 集合多种类型知识的方法 | 词汇 句法语义 | 机器学习相似度 | 兼顾各类型知识性能最好 | 不适合没有训练语料的情况 |

# Parsing as Evaluation



- We proposed a novel MT Evaluation Metrics based on Dependency Parsing Model
- We use the reference translations as the training corpus to train a parser
- The parser are used to parse the translation candidates
- The score of the parsing model obtained by the translation candidates are regarded as its quality score.

# WMT 2015 Metric Shared Tasks



| Correlation coefficient | Pearson Correlation Coefficient | | | | | | Spearman's |
|---|---|---|---|---|---|---|---|
| Direction | fr-en | fi-en | de-en | cs-en | ru-en | Average | Average |
| DPMFCOMB | .995 ± .006 | .951 ± .013 | **.949** ± .016 | **.992** ± .004 | .871 ± .025 | **.952** ± .013 | .879 ± .053 |
| RATATOUILLE | .989 ± .010 | .899 ± .019 | .942 ± .018 | .963 ± .008 | **.941** ± .018 | .947 ± .014 | **.905** ± .047 |
| DPMF | **.997** ± .005 | .939 ± .015 | .929 ± .019 | .986 ± .005 | .868 ± .026 | .944 ± .014 | .867 ± .050 |
| METEOR-WSD | .982 ± .011 | .944 ± .014 | .914 ± .021 | .981 ± .006 | .857 ± .026 | .936 ± .016 | .797 ± .062 |
| CHRF3 | .979 ± .012 | .893 ± .020 | .921 ± .020 | .969 ± .007 | .915 ± .023 | .935 ± .016 | .834 ± .068 |
| BEER_TREEPEL | .981 ± .011 | **.957** ± .013 | .905 ± .021 | .985 ± .005 | .846 ± .027 | .935 ± .016 | .827 ± .064 |
| BEER | .979 ± .012 | .952 ± .013 | .903 ± .022 | .975 ± .006 | .848 ± .027 | .931 ± .016 | .828 ± .061 |
| CHRF | .997 ± .005 | .942 ± .015 | .884 ± .024 | .982 ± .006 | .830 ± .029 | .927 ± .016 | .877 ± .051 |
| LEBLEU-OPTIMIZED | .989 ± .009 | .895 ± .020 | .856 ± .025 | .970 ± .007 | .918 ± .023 | .925 ± .017 | .857 ± .055 |
| LEBLEU-DEFAULT | .960 ± .015 | .895 ± .020 | .856 ± .025 | .946 ± .010 | .912 ± .022 | .914 ± .018 | .813 ± .071 |
| BS | −.991 ± .008 | −.904 ± .019 | −.800 ± .029 | −.961 ± .008 | −.569 ± .042 | −.845 ± .021 | −.758 ± .054 |
| USAAR-ZWICKEL-METEOR-MEDIAN | n/a | .934 ± .016 | .935 ± .019 | .973 ± .007 | .891 ± .024 | .933 ± .016 | .849 ± .044 |
| USAAR-ZWICKEL-METEOR-MEAN | n/a | .945 ± .014 | .921 ± .020 | .982 ± .006 | .866 ± .026 | .929 ± .016 | .833 ± .041 |
| USAAR-ZWICKEL-METEOR-ARIGEO | n/a | .945 ± .014 | .921 ± .020 | .982 ± .006 | .866 ± .026 | .929 ± .016 | .833 ± .041 |
| USAAR-ZWICKEL-METEOR-RMS | n/a | .949 ± .014 | .895 ± .023 | .982 ± .006 | .815 ± .030 | .910 ± .018 | .821 ± .039 |
| USAAR-ZWICKEL-COMET-RMS | n/a | .834 ± .023 | .847 ± .027 | .869 ± .014 | .603 ± .041 | .788 ± .026 | .665 ± .069 |
| USAAR-ZWICKEL-COMET-ARIGEO | n/a | .805 ± .025 | .811 ± .030 | .837 ± .016 | .626 ± .040 | .769 ± .028 | .684 ± .063 |
| USAAR-ZWICKEL-COMET-MEAN | n/a | .805 ± .025 | .811 ± .030 | .837 ± .016 | .626 ± .040 | .769 ± .028 | .684 ± .063 |
| USAAR-ZWICKEL-METEOR-HARMONIC | n/a | .542 ± .034 | .553 ± .046 | .712 ± .021 | .407 ± .047 | .554 ± .037 | .770 ± .059 |
| USAAR-ZWICKEL-COMET-HARMONIC | n/a | .463 ± .036 | .511 ± .047 | .614 ± .024 | .406 ± .047 | .498 ± .038 | .596 ± .068 |
| USAAR-ZWICKEL-COMET-MEDIAN | n/a | −.116 ± .044 | .230 ± .051 | .644 ± .025 | .183 ± .054 | .235 ± .043 | .209 ± .092 |
| PARMESAN | n/a | −.219 ± .043 | .437 ± .047 | .328 ± .035 | .105 ± .055 | .163 ± .045 | .071 ± .080 |
| USAAR-ZWICKEL-COSINE2METEOR-MEDIAN | n/a | −.236 ± .042 | .014 ± .051 | .509 ± .028 | .102 ± .055 | .097 ± .044 | .048 ± .091 |
| USAAR-ZWICKEL-COSINE2METEOR-MEAN | n/a | −.115 ± .044 | −.337 ± .049 | .450 ± .029 | .318 ± .051 | .079 ± .043 | .086 ± .095 |
| USAAR-ZWICKEL-COSINE2METEOR-ARIGEO | n/a | −.115 ± .044 | −.337 ± .049 | .450 ± .029 | .318 ± .051 | .079 ± .043 | .086 ± .095 |
| USAAR-ZWICKEL-COSINE2METEOR-RMS | n/a | −.093 ± .043 | −.286 ± .052 | .406 ± .031 | .264 ± .052 | .073 ± .045 | .066 ± .087 |
| USAAR-ZWICKEL-COSINE-MEDIAN | n/a | −.409 ± .039 | −.502 ± .046 | .817 ± .019 | .072 ± .052 | −.006 ± .039 | −.082 ± .092 |
| USAAR-ZWICKEL-COSINE2METEOR-HARMONIC | n/a | −.355 ± .040 | −.117 ± .052 | −.090 ± .033 | .280 ± .053 | −.070 ± .045 | .099 ± .092 |
| USAAR-ZWICKEL-COSINE-RMS | n/a | nan | .008 ± .052 | .912 ± .013 | nan | nan | .122 ± .079 |
| USAAR-ZWICKEL-COSINE-MEAN | n/a | nan | −.048 ± .052 | .908 ± .014 | nan | nan | .111 ± .080 |
| USAAR-ZWICKEL-COSINE-HARMONIC | n/a | nan | −.159 ± .052 | .900 ± .014 | nan | nan | .034 ± .077 |

Table 1: System-level correlations of automatic evaluation metrics and the official WMT human scores when translating into English.

# Overview of Syntax in SMT

# Conclusion



- Syntax–based Translation Models
  - Constituent Tree-to-String Model
  - Forest-based Translation Approach
  - Dependency–based Model
- Syntax-based Language Model
  - Online Discriminative Structural LM for SMT
- Syntax-based Translation Evaluation Metrics
  - Dependency Parsing as Evaluation for SMT

# Future Work

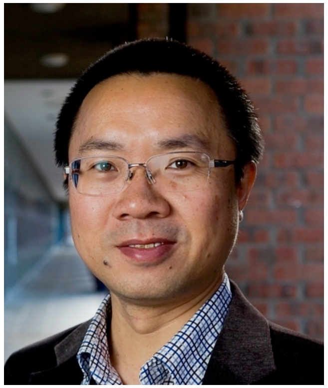


- Graph-based Translation Model
  - Sequence-based ➔ Tree-based ➔ Graph-based
  - A natural framework to incorporate various linguistic knowledge

    (1) n-gram (2) morphology

    (3) syntax (4) semantic
- Dependency Parsing as Evaluation for SMT
  - Extension to a discriminative model
  - Used as a combination framework

# Q&A

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